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TESIS DOCTORAL

Three Essays on Innovation

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Doctorado en Empresa y Finanzas

Departamento de Economía de la Empresa

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To my family

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Abstract

This dissertation consists of three empirical essays that investigate different topics within the field of innovation. The first paper focuses on the mechanisms available to firms to safeguard their intellectual assets in R&D alliances. When examining how to protect valuable technological assets from leakage in an alliance, prior research has largely focused on governance structure, alliance scope and, more recently, partner selection. In this paper, we view R&D employees that work side by side with R&D personnel of the partner as the critical juncture in safeguarding sensitive information, and consider the selection of inventors with specific characteristics of their embodied knowledge as an alternative response to hazards in R&D cooperation. Specifically, we claim that inventors who hold knowledge that is better protected against competitors' potential imitation represent a lower threat when technology leakage occurs. Consequently, we expect that managers will be prone to allocate these inventors into collaboration. By relying on patent ownership and authorship data, we analyze the allocation of inventors to collaborative projects from a sample of large pharmaceutical firms. Our results confirm that inventors are strategically allocated to projects according to their degree of preemptive power.

The second paper addresses the question of whether options trading enhances or impedes firm innovation, an important issue to policy makers as the eligibility criteria for securities in options trading are regulated by the Security and Exchange Commission (SEC). We argue that for firm that are listed on options markets, greater trading activity is associated with an increased propensity to innovate because they alter incentives for market participants to gather private information that is especially relevant for long-term investments and trading on such information makes stock prices more efficient. Because prices play an active role when managerial investment decisions are made, this should provide firm management with more incentives to engage in value enhancing innovative activities. We test our hypothesis on a sample of 548 publicly traded U.S. firms during the period from 1996 and 2004, and find that firms with more options trading activity generate more patents and patent citations per dollar of R&D invested, after accounting for other confounding factors. These results are confirmed when we use a propensity score matching procedure and an instrumental variable approach that account for the potential endogeneity of options trading. We then investigate how more active options markets affect firms' innovation strategy, and find that firms with greater trading activity pursue a more creative, diverse and risky innovation strategy. We discuss potential underlying mechanisms and show that options appear to mitigate managerial career concerns that would induce managers to take actions that boost short-term performance measures.

Finally, the third paper investigates the effect of obtaining a patent on the mobility of employee inventors who are at the beginning of their careers. We suggest that patents make human capital more specific to the employer and expect that patenting leads to lower levels of mobility. We use detailed micro data on applications filed at the U.S. Patent and Trademark Office (USPTO) since 2001 and approved or rejected before 2012. To establish causality, we leverage the fact that patent applications are assigned quasi-randomly to USPTO examiners and instrument for the probability that an application is approved with individual examiners' leniency. We document a negative causal effect of patents on inventor mobility: one additional patent granted decreases the probability of changing employer by about 25 percent. The estimated negative effect is nearly twice as large for discrete technologies (chemicals and pharmaceuticals) for which patent effectiveness is greater. The effect is also more pronounced in cases where the inventor's knowledge can be independently transferred (e.g., inventors with few co-authors) and for moves concerning technologically similar employers. Our results have implications for policies supporting knowledge diffusion through workers mobility.

Chapter 1

The Strategic Allocation of Inventors to R&D Collaborations

1.1 Introduction

Over the last few decades, inter-organizational research and development (R&D) partnerships have increased at a dramatic rate. From the early 1980s until the mid-2000s, the National Science Foundation (2010) reports an increase of 350 percent in the number of technology alliances formed by U.S. and multinational companies, the majority being non-equity based agreements. Interestingly, the sector that represents the bulk of these alliances from the early 2000s is biotechnology. In related industries such as pharmaceuticals, big players like Merck started at the beginning of the 2000s to aggressively pursue alliance opportunities to feed its pipeline.

It is a well-established fact that a firm taking part in an alliance faces a delicate trade-off regarding the type and amount of information it shares with its partner. On the one hand, the firm has to share knowledge in order to contribute to the success of the alliance. On the other hand, it has to safeguard critical knowledge so that its partner cannot take advantage of it to compete in the future. Unintended information leakage is a tangible risk that firms face in collaborations and, therefore, a challenge in the management of alliances. This dilemma is especially relevant in R&D collaborations, where knowledge sharing is a central part of the alliance. Previous literature has emphasized different instruments that help to mitigate the aforementioned risk. One is partner selection, where trust is paramount (Gulati, 1995). Another is the choice of the scope of the alliance (Oxley and Sampson, 2004), by which exposure of critical knowledge can be limited. Last, but not least, is the design of alliance governance mechanisms, ranging from the choice of the organizational form (joint ventures vs. contractual arrangements) to the implementation of hierarchical controls and administrative bodies that regulate the alliance (Reuer and Devarakonda, 2012).

In this paper, we focus on one key decision concerning the protection against the consequences of unintended knowledge leakage in R&D alliances: the selection of the participating employees. We view R&D employees (i.e., inventors) working hand in hand with the R&D employees of the partner firm as the critical factor in safeguarding sensitive information in an R&D alliance. We suggest that the type of knowledge embodied by inventors affects the threat posed by unintended information leakage. Specifically, we claim that inventors who hold knowledge that is better safeguarded against potential imitation by competitors represent a lower threat in the event that technology leakage occurs. Therefore, we expect that managers will tend to allocate such inventors to collaborative projects.

Previous research acknowledges that employees are an important conduit for unintended sharing of knowledge in cooperative agreements. In a series of case studies on alliances, Hamel, Doz, and Prahalad (1989) first note that operating employees in the front line determine the information that gets traded. Oxley and Wada (2009) and Reuer and Devarakonda (2012) state that uncodified know-how may leak through informal interactions between the personnel involved in an R&D alliance. Participating firms try to control these flows of information between employees and, therefore, the associated potential unintended knowledge leakage. In particular, previous literature points to the use of different types of formal and informal practices, committees or organizational structures that aim to control the amount and type of information that is shared with the alliance partner (among other objectives). Hamel, Doz, and Prahalad (1989) underline the importance of implementing practices such as advising employees about the valuable information that should not be shared. Oxley and Wada (2009) suggest that alliances organized as joint ventures make it possible to enforce employee conduct rules and manage employee movements, thus limiting informal interactions. These types of monitoring mechanisms can also be replicated in non-equity alliances through the creation of committee structures (Reuer and Devarakonda, 2012). However, to date the literature has not addressed the strategy of directly intervening in the selection of employees in order to mitigate the risk of leakage. This is despite the fact that innovation studies have shown that inventors play a key role in inter-organizational knowledge transfer and, consequently, in firm learning and innovativeness (Agrawal, McHale, and Oettl, 2014; Almeida and Kogut, 1999; Nerkar and Paruchuri, 2005; Palomeras and Melero, 2010; Paruchuri, 2010; Rosenkopf and Almeida, 2003; Singh, 2007; Song, Almeida, and Wu, 2003). Therefore, a closer examination of the inventors that participate in R&D collaboration appears to be a promising direction to address the risk of misappropriation and knowledge leakage.

Studies on inter-organizational knowledge exchange at the individual level are rare. Existing contributions focus on self-reported individual characteristics and outcomes. In an unpublished paper on the medical devices industry, Lofstrom (2000) collects data on at least one key R&D worker from each partner involved in an alliance, and studies several factors that influence the extent to which individuals learn through alliances. His main finding suggests that learning is related to individuals' social and human capital. In a recent dissertation, Wang (2015) takes a network perspective to examine individual performance using employee survey data from an alliance between a company producing fuel cells and a research institute. Her conclusions underline the importance of job experience, centrality in the formal network and motivation as determinants of individuals' contribution to the alliance. These pieces of research, nevertheless, take teams of employees participating in alliances as given. Unlike our study, they do not address the risk of technology leakage nor the decision to allocate particular employees to alliances.

This paper contributes to the literature on R&D alliances, specifically to the stream that focuses on the mechanisms that partner firms use to minimize the risk of information leakage. We posit that firms going into collaboration select inventors who hold knowledge that is more protected because, in the event of leakage, the competitor will not be able to use this knowledge effectively. To the best of our knowledge, this is the first systematic study that analyses R&D alliances from an individual perspective, i.e., taking as the unit of observation the researchers involved in such collaborations. To this end, we rely on inventor data retrieved from patent documents in the pharmaceutical industry, where collaborations are frequent and innovative output is usually patented. Patent documents allow us to detect: (i) collaborative projects through co-assignments, i.e., patents where more than one institution share the patent holder rights, (ii) inventors participating in these co-assigned patents, and (iii) characteristics of the inventors' knowledge background, including the degree of protection afforded by the patents protecting their innovation portfolio. We examine a sample of large pharmaceutical firms and their patenting activities from 1990 to 2005. Our results suggest that inventors whose knowledge has a higher degree of preemptive power, i.e., that is more protected against potential inventing-around by competitors, are more likely to be allocated to collaborative activities. We find that this effect is more salient for central inventors in the intra-firm co-inventing network and more pronounced when the partner is less trustworthy. These findings suggest that the allocation of inventors is an important factor for reducing the information leakage risk associated with an alliance. Finally, we examine the performance implications resulting from the collaboration and find that the participation of inventors with higher preemptive power is associated with higher-quality innovation outputs. We theorize that this is because of an increased willingness to efficiently share knowledge between partners, since appropriability concerns and uncertainties involved in information sharing are mitigated.

1.2 Theoretical framework

One of the main concerns for innovative firms is the risk of not being able to appropriate the returns of their investment in R&D. One of the determinants for this risk is the competitors' ability to replicate knowledge (Teece, 1986). Thus, when a firm engages in an alliance and exposes some of its body of information to its partner (part voluntarily and part unintendedly), it is likely that the partner learns how to replicate this knowledge, undermining the originating firm's appropriability. This is a real risk that firms face when entering into an alliance and something they have to weigh against the value of the synergistic knowledge that the alliance can yield (Arora and Merges, 2004; Katila, Rosenberger, and Eisenhardt, 2008). The firm's decision to enter into an alliance will largely depend on its ability to minimize this threat. This, in turn, depends on two factors: (i) preventing/reducing leakage of alliance-unrelated knowledge, and/or (ii) preventing partners from using knowledge that has been transferred voluntarily or involuntarily.

Avoiding leakage is a matter of constricting knowledge flows to those strictly related to the success of the alliance. This is achieved by organizational structures that can establish mechanisms for tightly controlling the knowledge that flows to the partner (Oxley and Wada, 2009; Reuer and Devarakonda, 2012). These mechanisms are designed to control the activity of managers and operating employees who interact with the partner and who are the actual conduits for the transfer of information (Hamel, Doz, and Prahalad, 1989; Janowicz-Panjaitan and Noorderhaven, 2008). The sharing of information can be easily monitored when it is contained in (and, therefore, probably also transferred through) blueprints and other documents. If the information is non-codified, it is more difficult to establish boundaries to its transfer. This is especially the case if this knowledge involves tacit elements. The tacit dimension of a given piece of knowledge is usually transmitted inherently when working together with the individuals who embody it – these can be the creators of the underlying knowledge or other individuals who learned it through interactions with the creators or previous learners (Zucker, Darby, and Torero, 2002). Therefore, in organizationally embedded collaborations, where individuals from both partners interact repeatedly in an organizational setting, tacit know-how is easily transmitted across firm boundaries (Kogut, 1988). This makes it difficult to limit its flow and even to realize the extent to which it is being transferred, making it especially prone to unintended leakage. Some alliance structures such as joint ventures constrain knowledge sharing to strictly formalized channels, and, consequently, limit tacit knowledge flows to the strict domain of the alliance (Oxley and Wada, 2009). Ultimately, nonetheless, the knowledge embodied by the personnel directly involved in the alliance is the key determinant of the potential risk of knowledge leakage. Their tacit knowledge, both related and unrelated to the alliance, is almost inevitably exposed to the partner (Oxley and Sampson, 2004). Consequently, the assignment of R&D personnel to alliances plays a crucial role in determining the knowledge that the firm puts at risk.

The extent to which leakage can harm the firm will depend on whether competitors end up using this knowledge. Firms involved in an alliance have a range of options to prevent partners from using the transferred knowledge to compete outside the alliance. One of these mechanisms is to select a partner the firm can trust. This would typically involve either an actor who has developed a strong reputation as a reliable collaborator (Gulati, 1995; Li, Eden, Hitt, and Ireland, 2008) or some player who has less incentives to appropriate other firm's knowledge because of limited opportunities outside the focal alliance (Diestre and Rajagopalan, 2012). Another mechanism is the use of formal intellectual property protection. Patents, in particular, make transactions in the market for technology smoother because parties are protected against appropriability hazards (Arora, Fosfuri, and Gambardella, 2001). Having the firm's technology patented also affects the likelihood of engaging in different types of cooperative agreements, as Gans, Hsu, and Stern (2002) point out for the case of start-ups. In a more macro perspective, the effectiveness of intellectual property protection in a given sector seems not to significantly affect the likelihood of cooperating (Bönte and Keilbach, 2005), but it significantly reduces the likelihood that an alliance will fail (Lhuillery and Pfister, 2009). According to Oxley (1999), in the absence of effective protection of intellectual property rights, firms are likely to use other mechanisms, such as hierarchical governance forms, to give the partner the right incentives with respect to the use of the counterparty's technology.

The strength of an individual patent depends on its power to keep competitors at a distance in the technological space, meaning that their products will be well differentiated. This power is determined both by the intrinsic characteristics of the underlying technology (Cohen, Nelson, and Walsh, 2000) and by the firm's patenting strategy. Firms, for instance, may decide to patent broad claims or to build "patent fences" by patenting close substitutes in order to deter competitors' entry into the market (Ziedonis, 2004), which is commonly referred to as "preemptive patenting." Ceccagnoli (2009) shows that both the effectiveness of protection that a patent confers against the imitation of the firm's innovations and the firm's use of preemptive patenting increase the market valuation of its R&D assets. In the same line, Czarnitzki, Hussinger, and Leten (2011) suggest that patents that effectively block competitors confer an important competitive advantage to their owner, which translates into a substantial boost of the firm's market value. Findings by Grimpe and Hussinger (2014) indicate that this competitive advantage also generates a higher valuation of the firm if it becomes a target in the market for M&As. Therefore, we expect that in the context of alliances in which firms share knowledge with potential competitors, the preemptive power associated to this knowledge is especially relevant as a protection mechanism against its appropriation by competitors.[1]

To sum up, we know that, on the one hand, the knowledge embodied by the R&D personnel assigned to alliances is what the firm puts at risk in the collaboration. This selection is, in

[1] Note that we use the term "preemptive power" to define the blocking power of patents, regardless of whether the firm purposely uses patents to preempt rivals or not.

turn, determined by the knowledge needs of the alliance but it likely includes other knowledge unrelated to it. On the other hand, we know that, if knowledge is covered by strong patents, its use by the competitor is effectively blocked. Therefore, even if leakage happens, the competitor will be unable to appropriate the returns from its partners' knowledge. Consequently, the more protected is the set of knowledge exposed to the partner, the lower is the threat posed by information sharing in general and unintended information leakage in particular. In this setting, the degree of protection of the knowledge embodied by a given R&D employee becomes a relevant factor in assessing the risk a firm incurs when allocating him to a collaborative project. Managers are thus likely to allocate those inventors to external collaborative projects whose knowledge set is strongly protected, i.e., has a high degree of preemptive power. Hence, the more protected is an inventor's set of knowledge, the more likely he is to be assigned to an external collaborative project that has to be staffed.

> *HYPOTHESIS 1 (H1): The greater the preemptive power of an inventor's set of knowledge, the more likely he is to be assigned to a collaborative project.*

If an inventor's preemptive power acts as a mean of protection in collaboration, we should observe that its effect on the likelihood that an inventor is allocated to a collaborative project is more relevant in situations where the risk of misappropriation by the partner is larger. We next propose two characteristics that entail different levels of misappropriation risk: (i) the centrality of an inventor in the intra-firm collaboration network, and (ii) the trustworthiness of the collaboration partner.

1.2.1 Inventor's structural centrality

Earlier research has shown that inventors who occupy a more central position the intra-firm co-inventing network have superior access to information and knowledge (Bonacich, 1987), a higher perception of their quality and a greater number of patent citations made to them (Podolny, 2001; Podolny, Stuart, and Hannan, 1996); moreover, they have a significant influence on the selection of the firm's technological path (Nerkar and Paruchuri, 2005) and a greater impact on the quality of their firm's innovative outputs (Paruchuri, 2010). On the one hand, these findings highlight the potential benefits that such inventors could bring for the success of a collaboration, in terms of highly valuable contributions. On the other hand, their central position is associated with substantial challenges in terms of the risk of technology leakage. Specifically, their access to a large amount and variety of internal information increases the risk that critical information is exposed to the partner. At the same time, the amount of knowledge they put at risk reduces the decision makers' ability to identify and control unintended transfers of important knowledge to collaboration partners (Hwang and Lin, 1999; O'Reilly, 1980). In contrast, inventors occupying a less central position have (and can, therefore, potentially expose to the partner) a far smaller amount of information, which managers are also better able to assess and control. These conflicting effects related to an inventor's degree of centrality prevent us from making an unequivocal prediction regarding the impact on his likelihood of being assigned to collaboration. However, the fact that centrality is associated with a higher leakage risk suggests that the role of preemptive power in collaborations is likely to be particularly large in the case of central inventors. Hence:

HYPOTHESIS 2 (H2): The effect of preemptive power of an inventor's set of knowledge on his likelihood of being assigned to a collaborative project is positively moderated by his level of centrality in the intra-firm inventive network.

1.2.2 Partner-specific and general collaboration experience

As previously mentioned, the selection of a trusted partner in a collaboration may help to minimize the risks of knowledge misappropriation in an alliance. Trusted partners are usually those who have developed a strong reputation in previous collaborations after multiple interactions either with the focal firm (Dyer and Singh, 1998; Gulati, 1995; Li, Eden, Hitt, and Ireland, 2008) or with other firms. Specifically, Hitt, Bierman, Uhlenbruck, and Shimizu (2006) reveal that prior ties with the focal firm are positively related to larger contracts in dollar value terms, suggesting that interactions over time lead to greater trust between partners. The network of collaborators in which a firm is embedded also internalizes information about the reliability and trustworthiness of a potential partner that interacts in the network (Gulati and Gargiulo, 1999). Moreover, the threat of reputational damage that a potential partner embedded in the network may face in the event of misappropriation provides disincentives to act opportunistically (Gulati and Gargiulo, 1999). In the specific setting of R&D collaborations in the pharmaceutical/biotechnology industry, Robinson and Stuart (2007) find that partners with stronger reputation in the community receive larger initial payments, less supervision and less detailed contracts when they engage in alliances. These findings suggest that reputation in the network leads to relationships based on trust, which allows to reduce control on the partner. This evidence conveys the idea that trusted partners reduce the need to guard against technology misappropriation risk. That is, even when the opportunity to act opportunistically may be available, reputed partners are more likely to refrain from doing so. Consequently, we expect that trust in an R&D collaboration should offset the need to allocate inventors with strong knowledge protection. In other words, since the consequences of knowledge leakage are much less dangerous in collaborations with known partners, firms will be less concerned about the degree of protection of the knowledge embodied by the inventors allocated to the collaboration. Conversely, alliances with unfamiliar collaborators pose higher risks of misappropriation, and, therefore, we posit that partners will seek greater protection of the knowledge exposed in the collaboration. Hence:

HYPOTHESIS 3 (H3): The preemptive power of an inventor's set of knowledge has a greater impact on the probability of his being assigned to collaborate with a non-trusted partner than with a trusted partner.

1.3 Data and methods

We chose to conduct our research in the pharmaceutical industry for several reasons. First, R&D collaborations are a significant feature of this sector (Arora and Gambardella, 1990; National Science Foundation, 2010). Second, patents are a meaningful measure of innovation in this industry given that they assure firms fairly strong protection of their intellectual assets (Cohen, Nelson, and Walsh, 2000). As prior research indicates, pharmaceutical firms tend to patent most inventions (Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches, 1987). Through their patenting activities, we can identify firms' R&D activities, both internal and in collaboration with others, and the inventors participating in them. Patent documents also allow us to track these inventors back in time in order to reconstruct their work history and characterize their knowledge background.

Our sample consists of the 27 largest pharmaceutical firms in terms of R&D spending. This sample was drawn from the 2006 EU industrial R&D investment scoreboard, which provides listings of the 1000 most R&D-intensive EU and non-EU firms across all manufacturing industries.[2] We use the Worldwide Patent Statistical Database (Patstat, April 2012 edition) to examine the patenting activities of these firms during the period 1990 – 2005. Given that we need to use comparable patent data across firms, regardless of their country of origin, and given that large pharmaceutical patent applicants usually seek broad international protection, we rely on the patents filed at the European Patent Office (EPO). Since we rely on information on the co-ownership of patent applications to detect collaborative innovation activities (see next section), European patent data have one specific advantage over the United States Patent and Trademark Office (USPTO) data. While, in both jurisdictions multiple owners have the right to exploit the patented invention for their own purposes, co-owners in most national legislations in Europe keep control over the joint property right because they need each other's permission to license the patent (this is not the case under the U.S. regime, where each owner can execute his rights without the consent of co-assignees).[3] For this reason, co-patenting is less popular in the U.S. than in Europe as Fosfuri, Helmers, and Roux (2012) underline, showing that the co-ownership of the same innovation is observed more frequently in Europe than in the U.S.

In order to reliably identify patenting activities that correspond to our sample firms, we need to trace each firm's history to account for any name change, acquisition, foundation or dissolution of entities as well as to identify all of its divisions, subsidiaries, and joint ventures.[4,5] We do so by using ownership links provided by Bureau van Dijk's (BVD) Amadeus database, 10-K reports filed with the Securities and Exchange Commission (SEC) in the U.S., corporate annual

[2] See http://iri.jrc.ec.europa.eu/scoreboard.html.

[3] See 35 U.S.C. 262 Joint owners and APPI's Group Reports Q194 for European countries.

[4] For example, by reconstructing the history of Novartis, we detect it was created through the merger agreement between Ciba-Geigy AG and Sandoz AG (dated 6 March, 1996), which were dissolved.

[5] Unfortunately, we had to exclude patent applications filed by joint ventures from our sample of patents because we were unable to allocate inventors to any of the individual firms forming the venture in most of the cases. In addition, most joint-venture patents are concentrated in a relatively small number of firms. Nonetheless, we use these patents to build the history of the participating inventors. We identify 216 patent applications assigned to joint ventures. Of these, around 66 percent were assigned to MSD Sharp & Dohme through their joint ventures with DuPont (DuPont Merck Pharmaceutical Company), Sanofi-Aventis (Merial) and Johnson & Johnson (Johnson & Johnson – Merck Consumer Pharmaceuticals).

reports, and conventional internet sources. We then retrieve all patents filed by these firms between 1985 and 2005 (we use the priority year) in the pharmaceuticals category according to the International Patent Classification system (IPC class A61K, excluding cosmetics A61K8/*). The sample of patents we analyze starts in 1990, even though we collected information from 1985 onwards because we need prior information to allocate inventors to firms (as explained below). Our initial sample comprises 27,473 patent applications by 445 patent holders (i.e., assignees) for the period between 1990 and 2005.

We are able to identify the inventors listed in our set of patents through the EP-INV dataset.[6] This dataset allows robust identification of individual inventors across EPO patent applications and granted patents published since 1978 (the start of the Patstat database), and, therefore, accurate identification of patenting histories, thanks to specific disambiguation algorithms for inventor data (see Pezzoni, Lissoni, and Tarasconi, 2014). In order to identify a given inventor as the employee of a given focal firm at a given point in time, we require him: (i) to be listed as inventor in at least one patent application where the focal firm is the only assignee in the previous five years (i.e., from $t-5$ to $t-1$), and (ii) not to be listed over the same time period in any other single-assigned patent application with another assignee (i.e., a non-focal assignee). Using these criteria, we identify a total of 10,448 inventors as R&D workers of our sample firms (representing 78 percent of the total number of inventors listed in our original sample of patents).[7]

1.3.1 Dependent variables

Co-assignment

Our main dependent variable, *co-assignment*, is designed to capture collaborative research activities. Co-assignment takes the value 1 if a given patent is co-assigned between one of our sample firms and another economic institution (e.g., firm, government-affiliated body, university, hospital or research institute) that is not part of the consolidated business group; and 0 otherwise.[8]

The evidence on the use of co-patenting underlines it as a significant phenomenon behind joint technology development, especially in industries with strong intellectual property regimes, such as chemicals and pharmaceuticals (Hagedoorn, 2003; Belderbos, Cassiman, Faems, Leten, and Van Looy, 2014; Hohberger, Almeida, and Parada, 2015). Co-patents, though, may also reflect mere IP sharing arrangements instead of actual collaboration (Belderbos, Cassiman, Faems, Leten, and Van Looy, 2014). In order to ensure that the co-patent status in our sample entails *real* collaborative efforts between partners, we retrieve additional information on R&D agreements for each pair of co-assignees. For each co-owned patent application, we determined whether it is the result of collaborative technology development efforts in several steps. First,

[6] The latest version is available at http://www.esf-ape-inv.eu/index.php?page=3.

[7] For robustness, we also used alternate ten- and three-year cut-off points. Our findings remain unaltered using those thresholds.

[8] Note that we also excluded patent applications that are jointly assigned solely with individuals. Patent applicant names referring to individual persons are identified by the patent allocation algorithm provided in Van Looy, du Plessis, and Magerman (2006).

we checked whether the entities in question have alliances on file in the SDC Platinum database. Otherwise, we manually checked corporate websites, SEC filings, industry and trade journals, and news reports.[9] Only co-patents for which we can identify a record of R&D collaboration are included in our final sample. Our extensive data collection efforts enabled us to identify 93 percent of all co-patent applications as the results of technological partnering activities.[10]

However, co-assigned patents are limited in the extent to which they can capture firms' collaboration behavior, since not all collective innovative efforts result in a joint patent. Survey evidence across Europe shows that 15 percent of patents are generated with external co-inventors while only around 6 percent are jointly filed by independent organizations (Giuri, Mariani, Brusoni, Crespi, Francoz, Gambardella, Garcia-Fontes, Geuna, Gonzales, Harhoff, Hoisl, Le Bas, Luzzi, Magazzini, Nesta, Nomaler, Palomeras, Patel, Romanelli, and Verspagen, 2007). However, Azzola, Landoni, and Van Looy (2010) identify, on average, 5 times more technological collaboration per region when using co-patent data than data on publicly announced R&D alliances reported in the widely used MERIT-CATI database.

Partner-specific and general collaboration experience

We follow prior literature and build two categorical variables that proxy for the partner's collaboration experience. We identify previous collaborations through past co-patenting activities, either with the focal firm or other firms. First, we compute *partner-specific experience*, as in Li, Eden, Hitt, and Ireland (2008). Specifically, we use the number of co-patents filed for by a given dyad in the past five years to categorize each partner either as a *stranger* or *friend*. The variable is set to 1 when the partner had no patent co-assigned with the focal firm in the past five years (*stranger*); 2 when they have at least one common co-patent in the past five years (*friends*); and 3 when the project is a *solitary* activity. Second, we compute the partner's *general collaboration experience*, similarly to Hoang and Rothaermel (2005). We employ the partner's number of unique collaborators (excluding the focal firm) for a period of five years prior to the focal observation, and then split the sample into partners with *low* (= 1) and *high* (= 2) *reputation* in the collaboration market based on the sample median (4 partners). This variable also takes a value of 3 when the project is a *solitary* activity.[11]

[9] For example, consider the shared ownership of patent EP1347979 with a 2000 priority date between Roche (focal firm) and Vernalis, an integrated biopharmaceutical company. Our search reveals that the two companies entered into a research collaboration in 1999 to develop novel 5-HT2C receptor agonists as potential drugs for the treatment of obesity. Similarly, Novartis (focal firm) and the University of Zurich have a history of research on nerve regeneration solutions (e.g., by blocking Nogo-A). These efforts are reflected in co-patent EP1572745 with priority date in 2002.

[10] We also repeated all our regression analyses with the less restrictive approach of including co-patents with no publicly information available. This yields similar results to those presented here.

[11] Note that, for collaborative interactions that involve two or more partners, we are not able to compute to compute the abovementioned variables, since each partner may have a different status. This, however, affects only 4 percent of co-patents in our sample (which are dropped for this part of the analysis).

1.3.2 Independent variables

Preemptive power

To test our theory, we need a measure that allows the decision maker to assess the extent to which an individual inventor's knowledge is protected. Our identification draws on information from the patent examination process at the EPO. Specifically, we exploit the fact that the EPO patent examiner prepares a detailed search report on the "prior art" upon which an invention is built in order to evaluate whether the patent application in question meets the patentability requirements.[12] The examination guidelines require that references to prior art are categorized according to their relevance for the patent application under examination, distinguishing between: (i) conflicting prior art, and (ii) relevant but non-conflicting prior art. In particular, the patent examiner indicates the nature of each piece of prior art with respect to the patent claims by assigning specific code letters, such as A, X or Y (Harhoff, Hoisl, and Webb, 2005).

In this regard, while so-called "A references" refer to the state of art that pose no threat to the novelty of claims in the application, X and Y citations are potentially harmful. "X references" indicate that the invention in question (or any of its individual claims) might not be considered to be novel if the referenced document is taken into account on its own. "Y references" are applicable if the invention (or any of its individual claims) might not be considered to involve an inventive step when the referenced document is combined with one or more other documents of the same category, such combination being obvious to a person skilled in the art (Criscuolo and Verspagen, 2008; Harhoff, Hoisl, and Webb, 2005). Hence, XY-type references refer to conflicting prior art and are considered as "blocking citations." The patent may still be granted in those cases because the conflict may reside in only some of its claims (this is usually the case).

Previous research has shown that patents citing prior art classified as an XY-type have a lower probability of being granted, are more often withdrawn by the applicant before the EPO has made a decision (Guellec, Martinez, and Zuniga, 2012), and have a higher probability of facing opposition after granting (Harhoff and Reitzig, 2004). The literature, therefore, concludes that XY-cited patents exhibit higher preemptive power than other patents. Czarnitzki, Hussinger, and Leten (2011) and Grimpe and Hussinger (2014) aggregate the share of XY-type citations received by the patents owned by a given firm in order to measure the firm's degree of preemptive power.

Similarly, in order to determine individual-level *preemptive power*, for every inventor i at every time t in our data, we take the number of XY-type citations that the individual inventor's patent portfolio receives with respect to the total number of citations received up to (but excluding) year t.[13] The variable's range is between zero and one. The larger the value of this variable, the higher is the extent to which inventors' patents blocked subsequent patent

[12] Patent applicants at the EPO are not required to report relevant prior art in the application. In consequence, about 90 percent of all patent citations in EPO patents are added by the patent examiner (Criscuolo and Verspagen, 2008). The search for prior art follows the *Guidelines for Examination in the European Patent Office*. These guidelines are available at http://www.epo.org/law-practice/legal-texts/guidelines.html.

[13] Patent equivalents filed at national patent offices are taken into account when calculating this measure. This is important because, if patent equivalents were ignored, the number of forward citations that a patent receives would be underestimated (Harhoff, Hoisl, and Webb, 2005).

applications, invalidating the novelty of (some of) their claims.

Inventor's structural centrality

To identify the position of a given inventor in the co-inventing network, we construct an inventor-by-inventor network, which has inventors as nodes and patents among inventors working in the same firm as ties. Following standard procedures, we use a three-year running window. Using the resulting matrix of the one-mode network of inventors, we compute the structural centrality for each inventor using the Bonacich (1987) power measure with standard Matlab code. This frequently used measure has the advantage that, in measuring the centrality of a focal inventor, it explicitly takes account of the centrality of other inventors that co-invent with the focal inventor (Nerkar and Paruchuri, 2005; Paruchuri, 2010). Due to the right-skewed distribution of inventor centrality, we use its natural logarithm as the main measure in our analysis.

1.3.3 Control variables

Our analysis employs several individual-related covariates that control for inventor characteristics (observable to the econometrician) accumulated from the beginning of his patenting life up to (but excluding) year t. Specifically, we include *ln(total patents)*, measured as the natural logarithm of the inventor's accumulated number of patents filed until t, to capture his productivity. In order to control for his experience, we measure *ln(experience)* as the logarithm of the difference in years between t and his first patent priority year. We code *firm patents* as the proportion of patents applied for by inventor i with the focal firm from his first year until t. We include this measure to account for any differences that might exist between research intensities at the focal firm and previous employers. We also control for *knowledge concentration*, measured as the Herfindahl index of the concentration of the inventor's prior patenting activity across IPC four-digit classes. To account for the inventor's collaboration environment, we include the extent to which inventor i, on average, co-invented with someone with whom he had never co-invented before (*new coinventors*) and the average number of prior collaborators (*team size*).

Inventors' ability to generate high-quality output may be related with their allocation to collaboration. Because collaborative research with external partners often entails substantial transaction costs (Gulati and Singh, 1998), managers may prefer to select workers who can generate particularly high-added value in order to maximize the returns on their investment. Simultaneously, high-quality inventors may be more likely to be the authors of innovations whose patents receive more blocking citations. To account for this, we include *citations received* (a standard proxy for quality), measured as the average number of citations received by the inventor's patents filed until year t.[14]

Because allocation decisions may also depend on whether the scientist innovates in a firm's core (or peripheral) technology areas, we control for his experience in the firm's core technology

[14] Since there might be concerns regarding systematic differences in citations received by patents from different years and fields, we also experimented with standardized citations (Hall, Jaffe, and Trajtenberg, 2001). However, using this alternative variable delivered similar results to the unadjusted variable presented here.

areas. We consider a technology as core if the patent that covers it is classified in an IPC seven-digit class which coincides with some of the most frequent classes in the firm's patent portfolio. We adopt an approach similar to Song, Almeida, and Wu (2003), and identify core classes as those with a frequency greater than 8 percent in a given five-year time window.[15] We code *experience in a firm's core technologies* as the proportion of the inventors' patents applied for with the focal firm that fall in its core classes.

Given that the allocation of R&D workers to collaboration may be affected by their ability to be on the technological frontier and to draw on external knowledge, we include two additional controls. First, we code *basicness* as the average number of non-patent literature (NPL) citations to total citations made by the inventor in the patents he filed up to t. NPL references have frequently been used as a proxy for the openness to new technological opportunities or for the strength of the science link (Narin, Hamilton, and Olivastro, 1997; Von Graevenitz, Wagner, and Harhoff, 2013). Second, to capture the degree to which scientists innovate by using knowledge that does not reside within their existing knowledge base, we converted the scope measure of Katila and Ahuja (2002) to the inventor-level. Thus, for every inventor at every spell, we construct *search scope* as the average proportion of the citations he made up to t that were not cited by his prior work.

Because inventors who have prior experience in inter-organizational research may be more likely to be re-assigned to this type of project, we introduce a dummy variable, *prior co-assignment*, that captures whether an inventor has participated in collaborative patenting activities in the previous five years (= 1; otherwise, 0).

Finally, to control for the inventor's expertise in specific technological areas related to pharmaceutical research, we include a set of 17 dummy variables for the subclasses (IPC seven-digit) nested within our main IPC four-digit class A61K. All regressions further control for a full set of firm dummies and year dummies. Year dummies refer to the priority year of the focal patent.[16] Thus, we explore how within-firm differences in inventor characteristics relate to within-firm differences in the assignment of inventors, allowing us to control for firm-level unobserved heterogeneity.

1.3.4 Analytical techniques

Our estimation techniques vary according to the nature of the dependent variables. First, we use probit models to examine the probability that a given inventor is assigned to a collaborative versus a stand-alone research activity (H1 and H2). The probit model is appropriate given the dichotomic nature of our main dependent variable: i.e., whether or not it is a *co-assigned* project. Second, we use multinomial logit models to analyze the likelihood of an inventor being allocated

[15] We also considered alternate cut-off points of 4 and 10 percent of the firm's portfolio. Our findings are robust to those thresholds.

[16] Alternatively, we use the (priority) year of the last patent application filed by the inventor before the focal patent in order to take into account the moment in which he finished his last project, and, therefore, became available for allocation to the focal project. This would address potential differences in the duration of collaborative versus stand-alone projects. This does not change our results. Furthermore, we get similar results if we use an exact matching procedure and consider a single-assigned inventor from the same firm to be a potential match (i.e., available for allocation) only if he applied for his last patent in the same year as the co-assigned inventors.

either to a stand-alone project or to a collaboration with a certain type of partner (*friend* vs. *stranger* or *high* vs. *low reputation* partner; H3). The multiple categorical (unordered) choices captured by this variable make this method necessary. In both cases, every observation corresponds to a patent-inventor pair. Because we need at least one cited patent during the inventor's prior patenting history to construct his degree of preemptive power, inventors with no citation to their previous patents are necessarily excluded from the analysis. This leaves us with a baseline sample of 26,790 inventor-patent observations on 5,297 unique inventors and 13,091 unique patents for our analysis. Standard errors are clustered by inventor to account for the non-independence of observations (Wooldridge, 2010).

1.4 Empirical results

In Tables 1.1 and 1.2, we provide summary statistics and pairwise correlations, respectively. Our inventors are productive: 15.7 patent applications over a mean patenting life of 9.7 years. On average, an inventor in our sample has a 2 percent probability of being allocated to a collaborative project at a given moment in time and has a blocking citation ratio (or preemptive power) of 0.47.

Table 1.1
Descriptive statistics

Variable	Mean	StdDev	Min	Median	Max	Observations
Co-assignment	0.02	-	0	0	1	26,790
Friend	0.29	-	0	0	1	499
Partner's partner	5.24	11.40	0	4	140	499
Preemptive power	0.47	0.27	0	0.47	1	26,790
Inventor centrality	4.19	4.60	0.10	2.57	43.59	26,790
Total patents	15.69	17.16	1	10	398	26,790
Experience	9.67	5.14	1	9	28	26,790
Firm patents	0.98	0.08	0.06	1	1	26,790
New coinventors	0.67	0.19	0.14	0.66	1	26,790
Teamsize	5.56	2.60	1.05	5.09	29	26,790
Citations received	1.69	1.70	0.01	1.25	45	26,790
Experience in firm's core technologies	0.66	0.37	0	0.83	1	26,790
Knowledge concentration	0.26	0.08	0.06	0.26	1	26,790
Basicness	0.25	0.16	0	0.22	0.95	26,790
Search scope	0.84	0.14	0	0.85	1	26,790
Prior co-assignment	0.16	-	0	0	1	26,790
Patent characteristics used in the "additional evidence" section						
Citations	3.52	4.69	0	2	118	13,091
Triadic filing	0.67	-	0	1	1	13,091
Backward patent citations	4.85	7.40	0	3	142	13,091
Non-patent citations	3.19	10.48	0	1	115	13,091
Number of IPC-4 classes	3.22	1.21	1	3	10	13,091
Number of inventors	5.12	3.26	1	4	32	13,091

Table 1.2
Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Co-assignment																			
2. Preemptive power	0.04																		
3. Ln(Inventor centrality)	-0.06	0.00																	
4. Ln(Total patents)	-0.04	-0.05	0.48																
5. Ln(Experience)	0.00	-0.08	0.03	0.50															
6. Firm patents	0.01	0.02	0.10	0.02	-0.20														
7. New coinventors	0.02	0.07	-0.15	-0.52	-0.29	-0.04													
8. Teamsize	-0.03	0.04	0.57	-0.03	-0.18	0.07	0.05												
9. Citations received	0.02	-0.04	-0.03	0.12	0.39	-0.10	-0.15	-0.03											
10. Experience in firm's core technologies	-0.04	-0.04	0.17	0.01	-0.01	0.07	-0.11	0.06	0.05										
11. Knowledge concentration	-0.05	0.02	-0.08	-0.16	-0.16	0.08	-0.01	0.00	-0.04	0.26									
12. Basicness	0.06	0.07	-0.13	-0.12	-0.04	-0.03	0.21	-0.05	-0.06	-0.35	-0.31								
13. Search scope	0.01	0.00	-0.15	-0.41	-0.15	-0.04	0.56	0.02	-0.18	-0.11	-0.02	0.14							
14. Prior co-assignment	-0.01	0.00	0.02	0.12	0.14	-0.06	0.01	-0.05	0.06	0.06	-0.06	0.03	-0.03						
Patent characteristics used in the "additional evidence" section																			
15. Citations	0.04	0.01	0.01	-0.04	-0.01	-0.01	0.03	0.04	0.06	0.05	0.02	-0.03	-0.01	0.00					
16. Triadic filing	0.01	-0.08	0.01	-0.01	0.00	0.03	-0.05	0.01	0.00	-0.02	-0.05	-0.01	-0.05	-0.09	0.12				
17. Backward patent citations	0.00	0.06	0.04	0.03	0.00	0.00	0.01	0.03	0.00	0.01	0.04	-0.03	0.01	0.02	0.05	0.00			
18. Non-patent citations	0.11	0.03	-0.04	-0.06	-0.04	-0.01	0.10	0.02	0.00	-0.20	-0.15	0.31	0.07	0.02	-0.01	-0.01	0.24		
19. Number of IPC-4 classes	0.07	-0.07	0.05	0.03	-0.02	0.01	-0.01	0.04	-0.03	-0.12	-0.41	0.24	-0.04	-0.05	0.05	0.21	-0.06	0.14	
20. Number of inventors	0.12	0.01	0.29	0.05	0.02	0.02	0.01	0.43	0.01	-0.01	-0.07	-0.01	0.01	-0.02	0.15	0.11	0.07	0.06	0.12

$N = 26,790$. All correlations above $|0.03|$ are significant at $p < 0.01$. The correlations in the lower part of the table correspond to the variables averaged across team members of the focal firm and are based on 13,095 team-patent observations.

Table 1.3 presents the specifications that test for our first hypothesis. Column 1 includes inventor-related control variables along with firm dummies, time dummies and technology class dummies. Column 2 adds our main variable of interest, i.e., *preemptive power*. The likelihood ratio test shows that the inclusion of this variable has a significant effect on the model's explanatory power. More specifically, the positive and significant coefficient estimate indicates that the more blocking citations an inventor's patent portfolio has received, the more likely he is to be assigned to collaboration, in support of H1. To give an idea of the size of this effect, the next two columns display the marginal effects at the means (MEMS) and the average marginal effects (AME). According to the marginal effects results in column 3, keeping the rest of independent variables at their means, an increase in blocking citations from 0 to 100 percent increases the probability of assigning an inventor to a joint project, on average, by 0.7 percentage points. Concerning the mean of the marginal effects predicted for all the observations of the sample (column 4), a shift from 0 to 100 percent in the blocking potential of an inventor's citation stock is associated with a 1 percentage point increase in the probability of being selected for collaboration. Given that the baseline probability of being assigned to collaborations is 2 percent, this is a result of economic significance.

In column 5, we differentiate between inventors' preemptive power according to the type of blocking citations. As mentioned earlier, blocking citations can be classified as X-type references (that question the novelty of the invention under investigation *if taken alone*) or Y-type references (that question the inventive steps claimed in the invention being examined, *when combined with one or more documents*). We follow this classification and compute the preemptive power variable for each of the two groups of references. X references represent 32 percent of our sample of inventors' total number of citations received and Y references represent 15 percent. In column 5, we see that the coefficient estimates for both variants of the preemptive power variable are positive. However, the coefficient of the type-X based preemptive power variable is significantly larger than in the case of the type-Y based variable (at the 10 percent level, F-test). According to the marginal effects at the mean of the rest of variables (unreported), an increase in type-X preemptive power from zero to one increases the likelihood of being assigned to a collaboration by 1.2 percentage points while in the case of type-Y preemptive power, this implies a 0.5 percentage point increase (average marginal effects indicate magnitudes of 1.8 and 0.7 percentage points, respectively). This suggests that X references, as citations that *directly* block claims in patent applications, reflect higher levels of preemptive power than Y references, and, therefore, have a larger effect on the predicted dimension.[17]

Turning to our control variables, we obtain some interesting insights from the analysis. The inventor's experience, in terms of the quantity of patents produced, *ln(total patents)*, has a negative effect on his selection for collaboration, while in terms of quality it has no effect (*citations received*). However, the percentage of patents with the focal firm (*firm patents*) has a positive effect. We find a lower likelihood of being assigned to collaboration when the inventor has a more specialized knowledge base in a certain technology field (*knowledge concentration*),

[17] This finding is in line with Harhoff and Reitzig (2004)'s who show that it is the increase in the number of X-type references that drives the effect of an increase in the likelihood that patents are attacked in opposition proceedings.

when he co-invents more frequently with new team members (*new coinventors*), when he worked in larger teams (*teamsize*) or when he has previously participated in co-assigned patents (*prior co-assignment*). This last result indicates that allocation decisions are not driven by a sequential allocation of those inventors that are experienced in inter-organizational research.

Table 1.3
Preemptive power and inventor allocation

Method	Probit	Probit	MEMS	AME	Probit
Dep. var.: Co-assignment (= 1)	(1)	(2)	(3)	(4)	(5)
Preemptive power		0.250**	0.007**	0.010**	
		(0.101)	(0.003)	(0.004)	
Preemptive power (Type X)					0.426**
					(0.172)
Preemptive power (Type Y)					0.175*
					(0.102)
Ln(Total patents)	-0.131***	-0.128***	-0.004***	-0.005***	-0.130***
	(0.045)	(0.046)	(0.001)	(0.002)	(0.046)
Ln(Experience)	0.028	0.040	0.001	0.002	0.025
	(0.064)	(0.064)	(0.002)	(0.003)	(0.066)
Firm patents	0.916***	0.871***	0.025***	0.037***	0.865***
	(0.319)	(0.319)	(0.009)	(0.014)	(0.319)
New coinventors	-0.405**	-0.410**	-0.012**	-0.017**	-0.425**
	(0.178)	(0.176)	(0.005)	(0.007)	(0.176)
Teamsize	-0.027**	-0.026**	-0.001**	-0.001**	-0.025**
	(0.013)	(0.013)	(0.000)	(0.001)	(0.013)
Citations received	0.018	0.020	0.001	0.001	0.018
	(0.012)	(0.012)	(0.000)	(0.001)	(0.012)
Experience in firm's core technologies	-0.016	-0.018	-0.001	-0.001	-0.019
	(0.100)	(0.100)	(0.003)	(0.004)	(0.100)
Knowledge concentration	-1.381***	-1.394***	-0.040***	-0.059***	-1.439***
	(0.489)	(0.488)	(0.014)	(0.021)	(0.491)
Basicness	0.073	0.060	0.002	0.003	0.070
	(0.184)	(0.185)	(0.005)	(0.008)	(0.184)
Search scope	0.005	0.027	0.001	0.001	0.016
	(0.218)	(0.221)	(0.006)	(0.009)	(0.219)
Prior co-assignment	-0.245**	-0.247**	-0.007**	-0.010**	-0.250**
	(0.105)	(0.106)	(0.003)	(0.005)	(0.106)
-2 Log Likelihood	4479.21	4468.07			4462.79
LR (χ^2)		11.14***			

$N = 26,790$. Number of unique firms: 27. Number of unique inventors: 5,297. Robust standard errors are clustered by inventor (in parentheses). All regressions control for a full set of firm dummies, priority year dummies and technology class dummies. The time period is 1990 – 2005. The Likelihood ratio (LR) tests for the increment in the overall model fit after including the preemptive power variable. "MEMS" are the marginal effects at the means corresponding to the probit coefficient estimates in column 2; "AME" are the average marginal effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We test our second hypothesis through the specifications presented in Table 1.4. Column 1 introduces the measure of inventor centrality and column 2 sequentially adds the multiplicative term with preemptive power. Including the interaction term improves the overall fit of the model and increases its explanatory power relative to the model shown in column 1. The positive and significant estimate of the interaction term suggests that the effect of preemptive power on the likelihood of being assigned to collaboration increases when the inventor occupies a more central position, as posited in H2. Panel A of Fig. 1.1 explores the conditional effect of preemptive power contingent on two different levels of the moderating variable (and all other variables set at their sample means): (i) high centrality (which corresponds to one standard deviation above its mean value or a value of ln(inventor centrality) of 2.01), and (ii) low centrality (which corresponds to one standard deviation below its mean value or a value of ln(inventor centrality) of -0.25). For the less central inventor, we observe that the probability of selection for collaboration increases moderately with the level of preemptive power. For the more central inventor, this increase is much steeper. While the difference between the two slopes provides indirect evidence in line with H2, it also suggests that both slopes (and the difference between them) change with the level of preemptive power. As Norton, Wang, and Ai (2004) and Hoetker (2007) point out, the interaction between two continuous variables in a non-linear model has different signs and magnitudes across observations. Accordingly, in Panel B of Fig. 1.1, we display the marginal effects of the interaction term for each observation in the sample. We find that they are positive for the vast majority of the sample, though not always significant, as shown in Panel C. Therefore, we obtain partial support for H2. For the sake of completeness, we also report the marginal effects at the mean (column 3) and the average marginal effects (column 4) of preemptive power when centrality (including the interaction term) is taken into account. Not surprisingly, these results are similar to those presented in Table 1.3.[18]

[18] Because inventor centrality is measured in its logarithmic forms, it takes negative values for the range between zero and one. In practice, this means that, for a small set of values, the *total marginal effect* of preemptive power may not be positive and significant. Computing the total marginal effect of preemptive power with respect to centrality (holding all other variables at their means) reveals that the effect is significant for the range of values from -0.36 (the 14$^{\text{th}}$ percentile of ln(inventor centrality)) to 3.77 (the maximum of ln(inventor centrality)) and positive across almost the entire sample (for values of ln(inventor centrality) $\geqslant -1.77$, or 98 percent of observations).

Table 1.4
Preemptive power, inventor centrality and inventor allocation

Method Dep. var.: Co-assignment (= 1)	Probit (1)	Probit (2)	MEMS (3)	AME (4)
Preemptive power		0.125^{*}		
x Ln(Inventor centrality)		(0.074)		
Preemptive power	0.251^{**}	0.223^{**}	0.008^{***}	0.011^{**}
	(0.101)	(0.099)	(0.003)	(0.004)
Ln(Inventor centrality)	-0.154^{***}	-0.205^{***}	-0.004^{***}	-0.006^{***}
	(0.037)	(0.052)	(0.001)	(0.002)
Ln(Total patents)	-0.017	-0.020	-0.001	-0.001
	(0.049)	(0.049)	(0.001)	(0.002)
Ln(Experience)	-0.005	-0.002	-0.000	-0.000
	(0.064)	(0.064)	(0.002)	(0.003)
Firm patents	0.873^{***}	0.884^{***}	0.024^{***}	0.037^{***}
	(0.310)	(0.310)	(0.009)	(0.013)
New coinventors	-0.281	-0.275	-0.008	-0.011
	(0.174)	(0.173)	(0.005)	(0.007)
Teamsize	0.013	0.012	0.000	0.000
	(0.014)	(0.015)	(0.000)	(0.001)
Citations received	0.017	0.017	0.000	0.001
	(0.012)	(0.012)	(0.000)	(0.001)
Experience in firm's core technologies	0.050	0.049	0.001	0.002
	(0.102)	(0.102)	(0.003)	(0.004)
Knowledge concentration	-1.421^{***}	-1.427^{***}	-0.039^{***}	-0.060^{***}
	(0.484)	(0.484)	(0.013)	(0.020)
Basicness	-0.005	-0.000	-0.000	-0.000
	(0.184)	(0.183)	(0.005)	(0.008)
Search scope	0.043	0.039	0.001	0.002
	(0.220)	(0.220)	(0.006)	(0.009)
Prior co-assignment	-0.251^{**}	-0.254^{**}	-0.007^{**}	-0.011^{**}
	(0.107)	(0.107)	(0.003)	(0.005)
-2 Log Likelihood	4439.51	4430.72		
LR (χ^2)	28.56^{***}	8.79^{**}		

$N = 26,790$. Number of unique firms: 27. Number of unique inventors: 5,297. Robust standard errors are clustered by inventor (in parentheses). All regressions control for a full set of firm dummies, priority year dummies and technology class dummies. The time period is 1990 – 2005. The Likelihood ratio (LR) tests for the increment in the overall model fit after including the inventor centrality variable and its interaction with preemptive power. Model 1 is compared with model 2 in Table 1.3, and model 2 is compared with model 1. "MEMS" are the marginal effects at the means corresponding to the probit coefficient estimates in column 2; "AME" are the average marginal effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

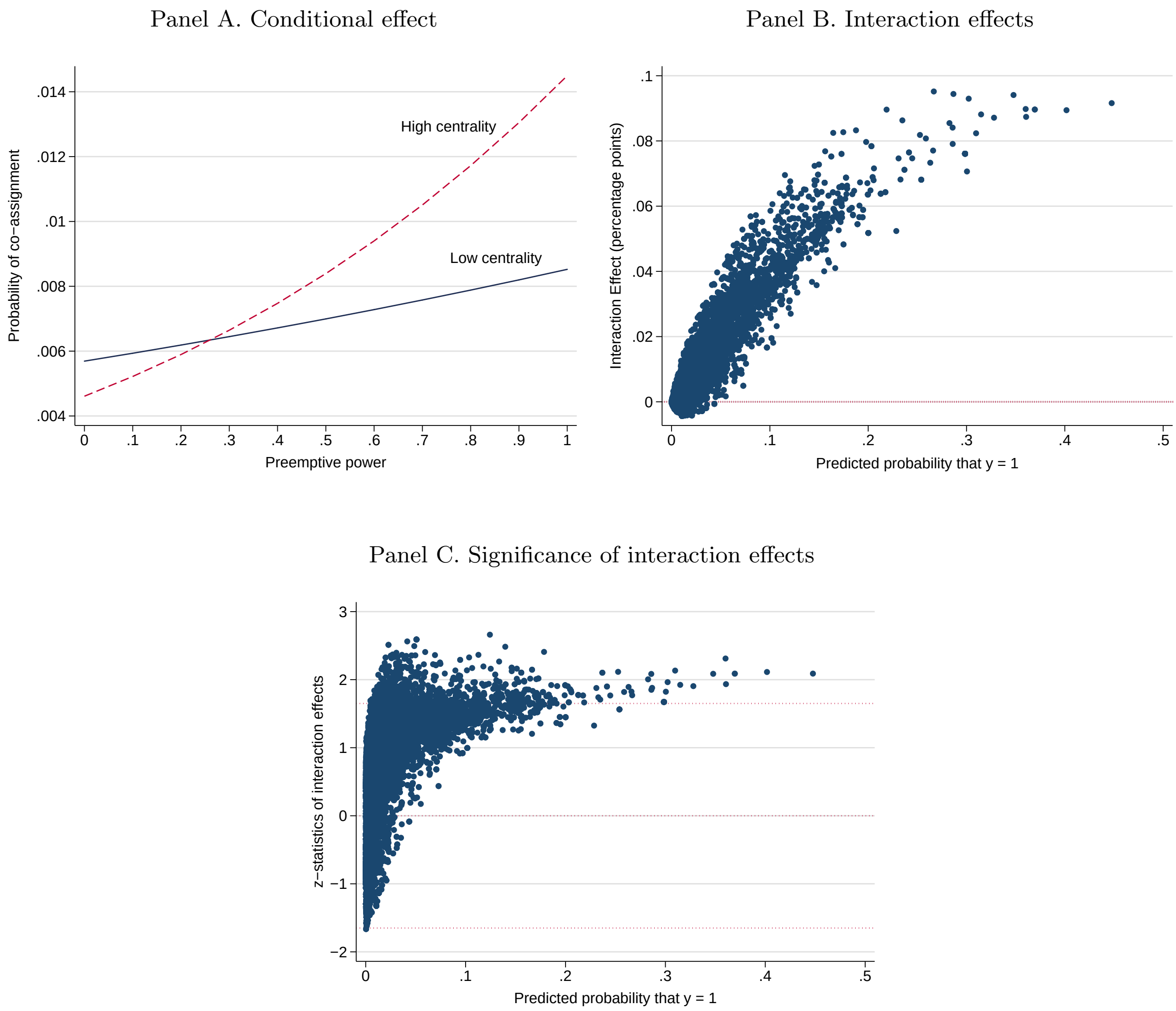

Fig. 1.1. Preemptive power and inventor allocation: the moderating effect of inventor centrality

Table 1.5 summarizes the results from the multinomial logit models that test for our third hypothesis. Panel A contains evidence related to partner-specific experience. The estimated coefficients compare the effect of being assigned to collaborative activities with either *friends* or *strangers* relative to *solitary* activities. The results show that the effect of preemptive power is to significantly increase the probability of allocating an inventor to a collaborative project with a stranger compared to the omitted solitary category. In terms of the relative risk ratio, the coefficient in column 1 implies that inventors whose blocking citation ratio increases from zero to one are more than twice as likely to be selected for collaboration with a stranger than an internal activity ($\exp(0.9) = 2.5$). The degree of knowledge protection, however, does not have a statistically significant effect on the likelihood of an inventor being allocated to a collaboration with a trusted partner (i.e., a friend). Changing the base outcome to strangers reveals that the difference between both coefficients is significant at the 10 percent level (not reported here). Panel B examines the relationship between inventor's preemptive power and the partner's reputation. The pattern of results is similar to that observed before. Specifically, the greater the preemptive power, the greater the odds of being allocated to a collaborative activity with a partner that has a lower reputation instead of an internal project, whereas the effect of preemptive power on the likelihood to collaborate is not significant in the case of partners with a stronger reputation. Again, the difference between both coefficients is significant at the 10 percent level. In sum, these findings represent strong support for H3, i.e., the degree of preemptive power of the knowledge set put at risk is more relevant in the allocation decision for collaborations with a higher perceived risk of opportunism, particularly those in which the partners are collaborators the firm does not trust.[19]

Table 1.5
Preemptive power, partner characteristics and inventor allocation

	Panel A: Partner-specific experience		*Panel B: Partner's general collaboration experience*	
Dependent variable	Stranger	Friend	Low reput.	High reput.
Method: Multinomial Logit	(1)	(2)	(3)	(4)
Preemptive power	0.900**	0.328	0.793**	-0.137
	(0.455)	(0.284)	(0.325)	(0.374)
Ln(Inventor centrality)	-0.205*	-0.209	-0.281**	-0.108
	(0.111)	(0.162)	(0.121)	(0.129)
Ln(Total patents)	-0.233	-0.451*	-0.188	-0.437**
	(0.148)	(0.245)	(0.161)	(0.193)
Ln(Experience)	-0.081	0.003	0.035	-0.141
	(0.194)	(0.265)	(0.203)	(0.246)
Firm patents	1.012	1.217	0.847	1.501
	(0.883)	(1.609)	(0.998)	(1.191)
New coinventors	-0.473	-2.131***	-0.646	-1.198
	(0.534)	(0.809)	(0.563)	(0.731)
Teamsize	0.032	0.034	0.053	0.003
	(0.046)	(0.069)	(0.047)	(0.049)
Citations received	0.063**	0.076**	0.043	0.088***
	(0.025)	(0.032)	(0.031)	(0.031)
Experience in firm's core technologies	-0.536*	1.252***	-0.416	0.546
	(0.306)	(0.476)	(0.332)	(0.391)
Knowledge concentration	-2.204	-8.415***	-2.756*	-5.332***
	(1.416)	(1.996)	(1.608)	(1.578)
Basicness	1.251**	-0.263	1.042*	0.553
	(0.522)	(0.812)	(0.552)	(0.654)
Search scope	0.046	1.006	0.232	0.153
	(0.650)	(1.053)	(0.704)	(0.903)
Prior co-assignment	-0.341	0.545	-0.233	0.081
	(0.276)	(0.353)	(0.279)	(0.334)

$N = 26,768$. Number of unique firms: 27. Number of unique inventors: 5,292. Robust standard errors are clustered by inventor (in parentheses). All regressions control for a full set of firm dummies, priority year dummies and technology class dummies. The time period is 1990 – 2005. The comparison baseline in both panels is "solitary." * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Thus far, our results indicate that the degree to which an inventor's knowledge is protected

[19] In unreported extensions, we also distinguish between collaborative activities with industry partners and universities (or research institutes). This generates very similar predictions for the pattern of inventor selection for collaboration discussed here. According to Belderbos, Cassiman, Faems, Leten, and Van Looy (2014), we may expect that the risk of leakage plays a more limited role in partnerships with universities since they are less likely to exploit and commercialize technologies. In line with the evidence presented above, repeating the specification of Table 1.5, the results show that preemptive power has a significant, positive coefficient of 0.579 (standard error of 0.304) when collaboration with firms is compared to solitary activities and a non-significant coefficient when comparing collaboration with universities to solitary activities (a coefficient of 0.010 with a standard error of 0.437).

plays an important role in inventor selection for collaborative research activities. We find evidence that is broadly consistent with the conjecture that an inventor's preemptive power is a mechanism that reduces the risk associated with information leakage in collaborations. In particular, our findings suggest that the effect of preemptive power on the likelihood of being assigned to a collaboration is greatest precisely in those cases in which the risk associated with the collaboration is greatest (i.e., more central inventors and collaborations with non-trusted partners).

1.4.1 Additional evidence

In this section, we provide supplementary evidence that helps to support our hypotheses. Specifically, we analyze whether the allocation of inventors with preemptive power enhances or diminishes the quality of collaborative innovation outputs. Examining the performance implications of inventor selection for collaboration strengthens our findings in two dimensions. First, it provides evidence that is consistent with the role of preemptive power as a facilitator of collaborative research. Second, it allows us to partially address a potential concern related to our concept of preemptive power, i.e., that it may capture an unobserved dimension of inventors' quality.

Related to the first point, previous work identifies the ability and willingness to transfer knowledge as the most important determinants of joint R&D performance (Sampson, 2007). Since knowledge transfer is subject to appropriation risk, firms are usually reluctant to contribute substantially to the pool of knowledge that is shared with the partner. Thus, even if the firm is able to transfer its capabilities or resources to partners, it is precisely the unwillingness to do so that may explain why inter-organizational research performance often falls short of expectations (Khanna, Gulati, and Nohria, 1998; Oxley and Sampson, 2004). In this context, we argue that the selection of inventors may affect how much value can be created in the collaboration, because this selection can influence the extent to which partners are willing to transfer knowledge-based capabilities. In particular, we propose that the assignment of R&D workers with preemptive power enhances the willingness of inventors (and their managers) to efficiently share knowledge between partners, since it substantially reduces appropriability concerns and uncertainties involved in information sharing. If preemptive power is a significant factor in diminishing knowledge leakage concerns in collaboration, we should then observe that the presence of inventors with high preemptive power leads to increased innovation performance.

To probe this conjecture, we focus on the allocation of teams of inventors and regress the value of the patented innovation on the interaction between the mean preemptive power of inventors working in the team of the focal patent and a dummy variable indicating whether the patent is co-owned. To measure patent value, we follow common practice by using the number of citations a patent receives (Hall, Jaffe, and Trajtenberg, 2005; Harhoff, Narin, Scherer, and Vopel, 1999). We compute all citations received by a patent (and its equivalents) with a fixed five-year window (labelled *cites*). Alternatively, we use *triadic*, a dummy variable that takes the value 1 if a patent is filed at the U.S., European and Japanese patent office (otherwise, 0). While patented technologies differ in their technical and economic value, triadic patent applications are a group of especially valuable inventions whose owners expect them to generate most profits as they are willing to incur higher filing and maintenance costs (Guellec and Van Pottelsberghe de la Potterie, 2008).

The empirical specifications include the average of inventor-related control variables across team members, firm dummies, and dummies for the year of the first patent application (i.e., priority year). Following prior studies on patent citations (Belderbos, Cassiman, Faems, Leten, and Van Looy, 2014; Fleming and Sorenson, 2004), we further control for the following patent-level characteristics: the number of *backward patent citations*, the number of *non-patent citations* (NPL references), the *number of IPC-4 classes* in which the focal patent is classified, and the *number of inventors* in the team responsible for the focal patent. The sample consists of 13,095 team-patent observations on 6,969 teams from our sample firms.[20] We apply poisson regressions to estimate the total number of forward citations and probit regressions for the probability of being a triadic patent. Standard errors are clustered at the team level.

The results are reported in Table 1.6. In column 1, we see that the coefficient on *co-patent* is positive and significant, suggesting that the total number of citations received by a collaborative patent is substantially higher than those received by a solo-assigned patent; this result confirms the finding of Belderbos, Cassiman, Faems, Leten, and Van Looy (2014). In column 3, however, we find that co-patents are not significantly associated with a greater likelihood of being filed as triadic patents. However, when we introduce the interaction between members' mean preemptive power and co-patent status, we observe that co-patents receive significantly more citations than solo patents *only* when the team members have a high enough value of preemptive power (for values of this variable $\geqslant 0.51$, or 42 percent of the observed distribution). For the 11 percent of observations with lowest values of preemptive power (for values $\leqslant 0.2$), the effect of co-patents on citations is significantly negative. For triadic as the dependent variable, the coefficient estimates suggest a similar pattern. In Panel B, we then restrict our sample to only co-assigned patent applications. Consistent with the results above, we find that the level of preemptive power of the average inventor in the focal team has a significant positive effect on the value of the resulting collaborative project. Specifically, a change in the focal firm's mean preemptive power from zero to one almost doubles the number of citations received (an increase of 97 percent) and it increases the probability of being filed as a triadic patent by approximately 24 percentage points.[21] In sum, the above evidence suggests that the allocation of inventors with high preemptive power to collaboration is positively associated with the quality of the collaborative output. We interpret this as supportive of the idea that inventors' preemptive power encourages knowledge sharing by reducing knowledge leakage concerns in collaborative research, consequently leading to higher value creation.[22]

As mentioned earlier, the findings from this section also address concerns that the preemptive power measure may capture an unobserved dimension of inventors' quality (i.e., some dimension

[20]Note that the number of team-patent observations (13,095) differs from the number of unique patents (13,091) because 4 patent applications are co-assigned between two of our sample firms.

[21]This latter figure corresponds to the estimated average marginal effect obtained from the specification in column 6.

[22]For robustness purposes, we also re-estimated the specifications in columns 2 and 5 with the dependent variable replaced by non-self-citations. The reasons is that self-citations may differ from other citations in various ways (Hall, Jaffe, and Trajtenberg, 2005). However, doing so leads to a similar conclusion.

not captured by the usual proxy for quality: the citations received on previous work). If this were the case, we should observe that the degree of inventors' preemptive power is, in general, a good predictor of the quality of the outcome of the focal project. However, that interpretation is hard to reconcile with our findings: specifications 2 and 4 of Table 1.6 show that the effect of members' mean preemptive power on innovation quality is not significant for solo-assigned patents. The fact that preemptive power affects only the value of co-patents but not of solo-assigned patents reinforces our argument that preemptive power is relevant for collaborative activities in order to create the trust needed to promote information exchange between partners. Importantly, this holds regardless of the measure of patent quality that we use.

Table 1.6
Preemptive power, inventor allocation and value implications

	Panel A: Full sample				*Panel B: Sub-sample of co-patents*	
Method	Poisson	Poisson	Probit	Probit	Poisson	Probit
Dependent variable	Cites	Cites	Triadic	Triadic	Cites	Triadic
	(1)	(2)	(3)	(4)	(5)	(6)
Members' mean preemptive power		0.446**		0.810**		
x Co-patent		(0.224)		(0.376)		
Members' mean preemptive power	0.028	0.008	-0.010	-0.036	0.978***	0.980**
	(0.052)	(0.054)	(0.067)	(0.068)	(0.197)	(0.402)
Co-patent	0.066**	-0.184***	-0.137	-0.579***		
	(0.027)	(0.063)	(0.094)	(0.186)		
Members' mean ln(inventor centrality)	-0.016	-0.017	0.024	0.024	0.186**	0.155
	(0.020)	(0.020)	(0.026)	(0.026)	(0.086)	(0.130)
Members' mean ln(total patents)	-0.025	-0.025	-0.057	-0.058	-0.328**	-0.558***
	(0.030)	(0.030)	(0.040)	(0.040)	(0.139)	(0.198)
Members' mean ln(experience)	-0.041	-0.040	0.073*	0.074*	0.312*	0.592**
	(0.036)	(0.036)	(0.044)	(0.044)	(0.186)	(0.279)
Members' mean firm patents	-0.119	-0.119	0.065	0.064	0.277	-1.302
	(0.149)	(0.149)	(0.175)	(0.175)	(0.764)	(1.674)
Members' mean new coinventors	0.268**	0.267**	-0.076	-0.077	-1.162**	-0.202
	(0.107)	(0.107)	(0.126)	(0.126)	(0.465)	(0.780)
Members' mean teamsize	-0.003	-0.003	0.008	0.008	-0.006	-0.061
	(0.009)	(0.009)	(0.013)	(0.013)	(0.030)	(0.048)
Members' mean citations received	0.039***	0.039***	0.003	0.004	0.066	-0.075
	(0.008)	(0.008)	(0.012)	(0.012)	(0.043)	(0.069)
Members' mean experience in firm's core tech.	0.122**	0.124**	0.074	0.076	0.320*	0.418
	(0.049)	(0.049)	(0.059)	(0.059)	(0.185)	(0.368)
Members' mean knowledge concentration	0.325*	0.320*	0.650***	0.638***	-1.210	0.078
	(0.174)	(0.173)	(0.214)	(0.213)	(1.242)	(1.348)
Members' mean basicness	-0.122	-0.121	-0.478***	-0.476***	-0.007	0.100
	(0.095)	(0.095)	(0.116)	(0.116)	(0.356)	(0.748)
Members' mean search scope	-0.346**	-0.346***	-0.449***	-0.448***	0.606	-1.046
	(0.134)	(0.134)	(0.166)	(0.166)	(0.554)	(0.957)
Members' mean prior co-assignment	-0.076	-0.076	-0.141**	-0.141**	0.266	-0.221
	(0.051)	(0.051)	(0.056)	(0.056)	(0.171)	(0.312)
Backward patent citations $_{patent}$	0.098***	0.099***	0.058***	0.059***	0.121	-0.031
	(0.019)	(0.019)	(0.022)	(0.022)	(0.110)	(0.142)
Non-patent citations $_{patent}$	-0.057***	-0.057***	-0.030*	-0.030*	-0.209**	0.130
	(0.017)	(0.017)	(0.017)	(0.017)	(0.099)	(0.099)
Number of IPC-4 classes $_{patent}$	0.202***	0.202***	0.590***	0.589***	-0.205	0.377
	(0.042)	(0.042)	(0.047)	(0.047)	(0.159)	(0.279)
Number of inventors $_{patent}$	0.376***	0.376***	0.261***	0.261***	0.850***	0.529***
	(0.025)	(0.025)	(0.027)	(0.027)	(0.117)	(0.177)
Observations	13,095	13,095	13,095	13,095	348	348
# of unique teams	6,969	6,969	6,969	6,969	253	253

Number of unique firms: 27. Robust standard errors are clustered by teams of inventors (in parentheses). All regressions control for a full set of firm dummies and priority year dummies. The time period is 1990 – 2005. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.5 Discussion and conclusion

Since the seminal publication by Hamel, Doz, and Prahalad (1989), inter-organizational research efforts have increasingly emphasized the need to protect proprietary knowledge from being exposed to partners. It is somewhat surprising, therefore, that so little research has addressed the issue of how the risk of technology leakage is related to *individuals* that participate in collaborations. This is especially relevant in the context of R&D collaboration where individuals from the two partners work together to produce new knowledge, exposing valuable tacit elements to their counterparty.

In this paper, we perform the first large-scale study of the assignment of R&D employees to external collaborations. By examining the patenting activities of the largest pharmaceutical firms, we are able to detect the contribution of inventors to firms' collaborative activities as reflected in co-assigned patents (compared with their participation in internal projects, reflected in solo-assigned patents). We document patterns that support the argument that managers select specific inventors for R&D collaboration in order to minimize the consequences of information leakage. Our central finding is that the probability that an inventor is assigned to an external collaborative project is positively associated with the strength of legal protection conferred by the property rights that cover the knowledge he (co-)created. This strong legal protection prevents the partner firm from effectively using any leaked knowledge to compete with the creator of such knowledge. We provide evidence that this effect is more significant for inventors who occupy a more central position in the intra-firm inventor network, and, therefore, whose contribution in an alliance entails a higher hazard due to the quantity and quality of information they hold. Our results also show that inventor's preemptive power is more important in cases where it is difficult to assess partners' trustworthiness, i.e., when the focal firm has had no previous relationship with the partner and/or when the partner has a lower reputation in the alliance market. Finally, we observe that external collaborative projects involving inventors with more blocking power generate more significant outputs, suggesting that greater protection may result in lower concerns about sharing knowledge, and, therefore, in more successful projects. Taken together, these findings yield some important contributions.

First, our analysis contributes to the literature on the management of alliances which stresses the importance of mechanisms that minimize the leakage of information in R&D collaboration. We add to this stream of literature by suggesting a widely neglected mechanism that may minimize the *consequences* of leakage: the selection of R&D employees for collaborations. While previous work underlines the role of employees in the unintended transmission of knowledge between partners and the importance of managing them properly in order to control knowledge flows, this paper proposes a new perspective on the actions that can be taken to manage employees involved in R&D alliances. The strategic allocation of inventors is a mechanism that can either complement or replace other means of knowledge protection, such as protective governance structures, scope restrictions or the selection of trustworthy partners.

Our results also have implications for the human resource management of R&D employees, in particular for the formation of teams. Our findings suggest that managers select inventors for certain projects (in our case external vs. internal projects) according to the fit between their characteristics and the requirements of the project. Particularly in large and medium-sized firms, where different R&D projects are conducted simultaneously, the allocation of R&D personnel across projects and the resulting teams may be a significant factor behind their success. To the best of our knowledge, our paper is the first to address the question of the allocation of inventors to projects, though in a very specific context.

This paper also adds to the literature on the role of intellectual property protection in the market for technology. Our results are aligned with the idea that strong protection facilitates the transfer of information, since fewer moral hazard problems can be expected. We take a new perspective and conceptualize the strength of protection held by an individual by looking at the (patented) innovations he contributed to. We provide evidence suggesting that individual-related preemptive power is an instrument that limits the threat of knowledge leakage in alliances, and, therefore, results in more effective sharing of knowledge between partners. It is plausible that inventors' preemptive power may also be an important determinant for other knowledge "transactions" in which the scientist is involved in the market for technology, including the market for inventors. We leave this to further research.

Though this study generates new insights into the role of inventors in collaborative R&D, our empirical strategy is subject to several limitations. First, the findings of this paper arise from the study of the largest firms in the pharmaceutical sector. This poses two limitations to the generalizability of our results, i.e., regarding firm size and industry. Our argument is based on the possibility of selecting inventors among those potentially suitable (who have the necessary expertise) for an alliance. This requires a set of inventors with partially overlapping knowledge backgrounds who could be allocated, without distinction, to collaboration. We assume that this is typically possible in large, but not necessarily in small, firms. Especially in the latter, this will depend on the degree of specialization of the firm and its R&D workers. Likewise, in other sectors where different mechanisms of knowledge appropriation prevail, preemptive power at the individual level may not confer protection against appropriation. Consequently, we should be cautious about generalizing the results. The second limitation concerns the use of patent data. Although patent data allow for an inventor-level analysis at a large scale that would otherwise be difficult to conduct and, in the case of pharmaceutical firms, they are the most comprehensive data of innovation activities, they present a series of drawbacks. One common downside in studies based on patents is that they only identify successful projects (i.e., those that achieved some output that qualifies for a patent). Another disadvantage, more specific to our study, is that they do not allow us to identify those collaborations that did not result in co-patents. This means that our pool of solo-assigned patents may contain some innovations that are in fact outputs of collaborative research. If there is no particular bias in the decision to co-patent the result of a collaborative project, this potential misclassification problem may lead us to identify an effect that is actually a lower bound for the actual effect. Note that, as we detail in the paper, we avoid the opposite source of misclassification, i.e., the existence of innovations resulting from solo-projects assigned as co-patents as the result of IP sharing agreements.

Our study focuses on the decision to allocate inventors to external collaborations only from the angle of the protection of technological assets exposed in the alliance. We neglect the opposite perspective, that is, organizational learning objectives which may also be relevant for inventor selection decisions. Although we account in our empirical analysis for some dimensions that may proxy for individual-level absorptive capacity, an extension of our study could focus on the learning side of knowledge transfer in collaborative R&D. Do firms learn more from partners when specific inventors are selected? If so, does the knowledge learned from these partners deplete over time because employees involved in collaboration leave the company?

Even with these limitations, we see our study as a first step to understanding the role played by individuals participating in R&D collaborations in the trade-off that firms face when they decide to engage in alliances. As Oxley and Sampson (2004) put it, when setting up an alliance, managers have to make a number of decisions: who to collaborate with, the scope of the alliance and the governance structure to adopt. In this paper, we suggest that managers make another relevant decision when defining a collaboration strategy: which inventors to allocate to the alliance.

Chapter 2

The Bright Side of Financial Derivatives: Options Trading and Firm Innovation

2.1 Introduction

Innovation is the main driver of growth and the wealth of nations. As emphasized by Porter (1992, p. 65), "[t]o compete effectively in international markets, a nation's businesses must continuously innovate and upgrade their competitive advantages. Innovation and upgrading come from sustained investment in physical as well as intangible assets." Given the importance of innovation for competitiveness, it is a priority to understand those factors that determine incentives to innovate at the firm level. There has been much debate on the role of financial markets in promoting innovation. While developed capital markets can improve the efficiency of long-term resource allocation through their monitoring and disciplining mechanisms, the need to meet quarterly or annual financial objectives gives rise to adverse externalities that may impair firms' incentives to innovate (Holmström, 1989; Porter, 1992).[1]

In this paper, we focus on one cornerstone of public equity markets, namely, financial derivatives. Specifically, we study whether the volume of equity options written on the underlying asset encourages or impedes firm innovation. Since the beginning of the new century, the total equity options volume traded on U.S. exchanges has grown exponentially, from 676 million contracts in 2000 to over 3,727 million contracts in 2015.[2] Unlike stock market listings, where firms apply, options listings are exogenous to firm decisions; they are made within exchanges. These exchanges are self-regulating institutions that are members of the Options Clearing Corporation (OCC), which operates under the jurisdiction of the Securities and Exchange Commission (SEC) (for exchange-listed options). Because the SEC plays an important role in determining the eligibility criteria for securities in options trading, this topic is of particular interest to policy makers.[3]

Did the significant rise in the volume of trading undermine innovative efforts or did it encourage firms to invest in innovation? We argue that for firms that are listed on options markets, greater trading activity is associated with an increased propensity to innovate. The literature suggests that active options markets alter incentives for market participants to gather private information that is especially relevant for long-term investments, and trading on such information makes stock prices more efficient (e.g., Cao, 1999; Chakravarty, Gulen, and Mayhew, 2004; Pan and Poteshman, 2006; Hu, 2014). If stock prices are more efficient, other types of (perhaps less-informed) investors learn more about the fundamental value of the firm, which reduces some of the asymmetric information problems connected to R&D. Because prices play an active role (i.e., managers learn from prices) when investment decisions are made, this should then provide firm management with more incentives to engage in value-enhancing innovative activities. The

[1] Laurence D. Fink, Chairman and Chief Executive Officer (CEO) of BlackRock, recently summed this up in a letter to Standard & Poor's 500 CEOs that BlackRock invests in (Business Insider, April 14, 2015): "Over the past several years at BlackRock, we have engaged extensively with companies, clients, regulators and others on the importance of taking a long-term approach to creating value. We have done so in response to the acute pressure, growing with every quarter, for companies to meet short-term financial goals at the expense of building long-term value. This pressure originates from a number of sources–the proliferation of activist shareholders seeking immediate returns, the ever-increasing velocity of capital, a media landscape defined by the 24/7 news cycle and a shrinking attention span, and public policy that fails to encourage truly long-term investment."

[2] See http://www.optionsclearing.com.

[3] See Mayhew and Mihov (2004) for initial listing requirements.

notion that informed agents in financial markets can ameliorate asymmetric information related to innovative activities is widely recognized in the literature (e.g., Hall and Lerner, 2010; Aghion, Van Reenen, and Zingales, 2013; He and Tian, 2013).[4]

In this paper, we focus on whether options trading spurs firm innovation in the context of R&D-intensive industries. We believe that these firms provide an ideal research setting for our study. For firms that invest more heavily in R&D, innovation is a core component of their competitive strategy, but they might also be forced to make only partial disclosure and be subject to a larger degree of information asymmetry (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). It follows that these firms are more likely to be undervalued by equity holders and have a greater exposure to hostile takeovers (Stein, 1988). Moreover, survey evidence obtained by Graham, Harvey, and Rajgopal (2005) shows that managers in technology-intensive industries are more prone to sacrifice long-term sustainability to meet desired short-term earnings targets, relative to managers in other industries, due to their personal wealth and career concerns. Those authors explain that meeting earnings benchmarks (particularly the earnings in the same quarter of the previous year) helps to maintain a firm's current stock price. Taken together, if the enhanced informational efficiency induced by options leads to better monitoring by reducing information asymmetries, making firms more willing to invest in innovation, we claim that this mechanism is particularly relevant for firms operating in R&D-intensive industries.

To test this conjecture, we assemble a rich and original data set containing time-varying information on standard measures of innovation based on U.S. patent data, R&D, options trading, governance, etc. To approximate the total annual dollar options volume, we use the approach proposed by Roll, Schwartz, and Subrahmanyam (2009). We run panel data regressions on a sample of 548 publicly traded U.S. firms during the period from 1996 to 2004. This sample consists of large firms that are active in five broadly defined high-tech sectors, where we observe high patenting propensities, and patents have been recognized as a meaningful indicator of innovation at the firm level (as explained in Section 2.3).

Our baseline test reveals a positive association between innovation and options trading. Options trading has a positive impact on R&D spending but a larger positive effect on the quality and/or productivity of R&D (i.e., citations per dollar of R&D invested). These results are robust to using alternative subsamples, alternative measures of innovation, the inclusion of a wide range of control variables, lagged explanatory variables, and several econometric models. While these findings are consistent with the beneficial effect of the production and aggregation of information in options markets, we have concerns that our results could be biased if informed agents trade on the basis of unobservable characteristics that are correlated with options volume and innovation. We account for such selection issues by weighting sample observations using their propensity score of having high levels of options trading and by estimating two-stage least squares (2SLS) models using moneyness and open interest as instrumental variables. Overall, our

[4] If we believe that informed agents can reduce information asymmetries related to innovative activities and that the stock market is an efficient resource allocation mechanism, then the "prospective role" (Dow and Gorton, 1997) whereby stock prices provide managers with information relevant for investment decisions could generate the same prediction. Our focus on the disciplining role of stock prices (as in Holmström and Tirole, 1993) is a natural choice for understanding the role of options trading in innovation, although we consider the two approaches to be complementary.

identification tests suggest that the positive correlation between options trading and innovation is not simply driven by self-selection.

We extend these baseline results in two main directions. First, we examine the link between options trading and three measures of innovative direction: (i) a measure based on the diversity of patents applied for by the firm across technological classes, (ii) the Hall, Jaffe, and Trajtenberg (2001) measure of patent originality, and (iii) a measure of risk-taking behavior based on the standard deviation of citations received across patents. The results suggest that more active option markets are associated with a change in direction and not just an increase in R&D spending and productivity.

Second, we attempt to identify the underlying economic mechanism through which this link occurs. Our results could be explained by two hypotheses. On the one hand, the results could be driven by the reasoning that poorly governed managers prefer to avoid the difficult decisions and costly efforts associated with innovation and that the information conveyed by more active options markets "forces" managers to innovate if they are a priori reluctant to do so [i.e., managers prefer the quiet life as in Bertrand and Mullainathan (2003)]. On the other hand, the results could be consistent with the prediction that increased monitoring "shields" managers against those reputational consequences [i.e., career concerns as in Holmström (1989, 1999)] that are more likely to occur when managers invest in innovation. Potential consequences occur because innovation involves a high probability of failure, and the innovation process is unpredictable and idiosyncratic, with many future contingencies that are impossible to foresee. In line with recent evidence obtained by Aghion, Van Reenen, and Zingales (2013) in the context of institutional investors, we find strong support for the career concerns story. We show that the positive effect of options trading on innovation is more pronounced when product market competition is more intense, when CEOs are less "entrenched," and for younger CEOs. Moreover, we provide evidence that the positive effect of more active options markets on innovation is magnified for firms that face a decline in profitability and remains substantial even after accounting for executive compensation schemes.

Although we follow standard procedures in using patent counts weighted by forward citations as a proxy for innovation, we must admit that one of the main limitations of our study is that we cannot completely exclude the possibility that our results may be partially driven by managerial signaling motives. This is because one common disadvantage in studies based on patents is that the latter are an indirect measure of innovation and contain no information on non-patentable inventions or inventions held in secrecy. We believe, however, that limiting our study to industries in which patenting represents the most important mechanism used by firms to protect their intellectual property for appropriability and/or strategic reasons mitigates such concerns.

While there is a growing literature that links a variety of financial market characteristics to innovation, to the best of our knowledge, such an analysis of the relationship between options trading and innovation has not previously been undertaken. Empirical studies have examined, for instance, the effect of institutional ownership on innovation (Aghion, Van Reenen, and Zingales, 2013), analyst coverage (He and Tian, 2013), credit supply (Amore, Schneider, and Žaldokas, 2013), stock liquidity (Fang, Tian, and Tice, 2014), leveraged buyouts (Lerner, Sorensen, and Strömberg, 2011), investors' failure tolerance (Tian and Wang, 2014), the decision to go public (Bernstein, 2015), and the development stage of financial markets (Hsu, Tian, and Xu, 2014). There is very little research on the role played by options (or more general financial derivatives) in the R&D process of publicly traded firms.

However, there is another paper that examines the possibility that active options markets are beneficial to the firm. Specifically, Roll, Schwartz, and Subrahmanyam (2009) find that options trading activity increases firm value through its impact on price informativeness. However, because greater informational efficiency tends to make an asset more valuable because it reduces the risk of investing in it, these results require further examination. Although several other studies also conclude that resources are allocated more efficiently if prices convey more information, which in turn leads to greater firm value (e.g., Khanna, Slezak, and Bradley, 1994; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Durnev, Morck, and Yeung, 2004; Chen, Goldstein, and Jiang, 2007), there is little empirical evidence of this effect on innovation. We view our study as complementary to Roll, Schwartz, and Subrahmanyam (2009) because we take option markets' effect on prices as given and aim to explain how this influences firms' incentives to innovate. Thus, the main contribution of our paper is to provide a direct link between options trading and the extent to which the firm allocates resources to innovation.

The remainder of the paper is organized as follows. Section 2.2 discusses the related literature in greater detail. Section 2.3 describes the sample, the measurement of variables, and descriptive statistics. In Section 2.4, we present our main results. In Section 2.5, we discuss the underlying mechanism through which options trading may affect innovation. Section 2.6 concludes the paper.

2.2 Related literature

Our paper borrows from different strands of the literature. Our starting point is the recognition that options stimulate informed trades and that the informational benefit of options depends on the trading volume. Almost 40 years ago, Ross (1976) was the first to argue that options trading can convey important information in a market with information asymmetry by expanding the contingencies that are covered by traded securities. Apart from reducing information asymmetry, Black (1975) notes that informed traders could use options markets as an alternative venue for trading because option contracts provide higher leverage. Easley, O'Hara, and Srinivas (1998) argue that options can be more attractive for informed traders because the availability of multiple contracts confronts uninformed traders with substantial challenges. In a similar vein, Cao (1999) suggests that agents with private information should be able to trade more effectively on their information in the presence of options, thereby improving price informativeness. Moreover, options are a mechanism for trading on information about future equity volatility, which allows investors with information about stock price volatility to benefit from options (Ni, Pan, and Poteshman, 2008). These notions are further supported by Chakravarty, Gulen, and Mayhew (2004) and Pan and Poteshman (2006), who find that options order flows contain information about the future direction of the underlying asset. More recently, Hu (2014) shows that an options-induced imbalance significantly predicts future stock returns. Taken together, these works provide strong support for the conjecture that informational efficiency may be greater in the presence of options.

A firm's informational benefit from options, however, should depend on the volume of options traded, beyond the presence of an options market on the firm's stock per se (as in Roll, Schwartz, and Subrahmanyam, 2009). For example, due to the maxim that "liquidity attracts liquidity," informed agents would be more willing to trade on their private information in markets with high trading volume because they are able to camouflage their trades (Kyle, 1985; Glosten and Milgrom, 1985). In contrast, if informed traders perceive a low-liquidity options market, they optimally desist from trading, and this belief becomes self-fulfilling (Admati and Pfleiderer, 1988; Chowdhry and Nanda, 1991). It follows that the enhancement of the benefit from listing should be directly related to whether the market for the listed options has sufficient volume because then informed traders would be more active.

Second, our paper builds on the literature that interacts information production (i.e., price informativeness) with investment decisions in firms. The idea that the production and aggregation of information as a consequence of trading between speculators and investors can be useful for the provision of incentives in firms is a relatively recent one. Specifically, Holmström and Tirole (1993) and Faure-Grimaud and Gromb (2004) examine the role of price informativeness in disciplining managers and providing incentives to insiders to engage in value-increasing activities. Dow and Gorton (1997) show that, in equilibrium, the information contained in stock prices can be used to guide investment decisions because managers are compensated based on future stock prices. Subrahmanyam and Titman (1999) study a setting in which investors may obtain information unavailable to firm insiders that is useful in making investment decisions. They show that if such information is freely available to outsiders, the firm chooses to go public. Empirically, for example, Durnev, Morck, and Yeung (2004) show that U.S. industries and firms exhibiting larger firm-specific return variation make better capital budgeting decisions. The findings in Chen, Goldstein, and Jiang (2007) suggest that firm managers learn from private information concerning their own firms' fundamentals contained in stock prices by incorporating stock price information into corporate investment decisions. Foucault and Gehrig (2008) show that cross-listing enables firms to obtain more precise information on the value of their growth opportunities, which allows managers to make better investment decisions. Finally, Ferreira, Ferreira, and Raposo (2011) provide evidence that if prices are more efficient, the stock market is able to play a monitoring role that can reinforce internal and external monitoring mechanisms, although the sign of this relationship is ambiguous (i.e., they can interact as either complements or substitutes).

Our particular focus is on how the enhanced informational efficiency induced by options affects managerial incentives to invest in innovation. Stein (1989) shows that even in rational capital markets, firms take actions to improve current earnings at the expense of lower future earnings in an attempt to misguide the market. Shleifer and Vishny (1990) offer a different argument that leads to the same conclusion. Because arbitrage is cheaper for short-term assets than for long-term assets, the latter must be more mispriced in equilibrium for net returns to be equal. It follows that managers may forgo investment opportunities in long-term projects because the uncertainty of these assets can take a long time to disappear. The empirical literature offers evidence consistent with managerial short-termism in publicly traded firms. For example, Asker, Farre-Mensa, and Ljungqvist (2015) find that compared to unlisted firms, listed firms tend to invest less and their investment levels are less sensitive to changes in investment opportunities. Bushee (1998) shows that firms are more prone to cut R&D in response to a decline in earnings when a very large proportion of institutional owners are investors that often trade in and out of individual stocks.

Based on the streams of literature reviewed above, we argue that a potential solution to the distortion of innovative investment due to agency problems is active options markets. The intuition is the following. In the presence of option market participants who engage in monitoring, informed agents move the stock price toward the fundamental value and thus cause it to more closely reflect the effort exerted by the manager to enhance long-term risky investment decisions. Because other financial market participants (especially firm investors) may have difficulties in properly evaluating managerial investment decisions in innovation (Stein, 1988), they can use stock prices as a signal of whether informed traders agree or disagree with the allocation of corporate resources and can decide whether to take action (as in Edmans and Manso, 2011). For example, if investors discover that the manager is good despite bad public information, they will be more willing to retain their shares because they will expect higher returns. Alternatively, they can directly use the threat of disciplinary trading and sell more given the discovery of negative information, causing the stock price to decline.

2.3 Data and methods

We examine the effect of options trading on innovation in the context of publicly traded U.S. firms in the following five industries: (i) pharmaceuticals (Standard Industrial Classification [SIC] code 283), (ii) industrial and commercial machinery and computer equipment (35), (iii) electronics and communications (36), (iv) transportation equipment (37), and (v) instruments and related products (38). A trade-off made in the design of our study was to limit the sample to these five industries and not to consider the entire manufacturing universe. We ensured that these industries represent a broad spectrum.[5] Nevertheless, we exercised caution in selecting these specific industries for several reasons. First, R&D has been and continues to be vital for the long-run competitive advantage of firms operating in these industries. In fact, these sectors have the highest ratio between R&D expenditure and net sales among all industries (Organisation for Economic Co-operation and Development, 2013). Second, these industries also form an apt context because of how they protect and document their inventions. Patenting (on which our dependent variables are based) is an important mechanism to protect intellectual property (Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches, 1987) and firms tend to patent most patentable inventions. In particular, Mansfield (1986) shows that our sample industries are characterized by high patenting propensities relative to most other industries. Third, patents are a meaningful measure of innovation in these industries. The association between patents and technological innovation is likely to be stronger in industries in which patents provide

[5]In 2004, these industries collectively included approximately 35% of all publicly traded U.S. manufacturing firms drawn from the Compustat database.

firms with fairly strong protection of their intellectual property.[6] Acs, Anselin, and Varga (2002) conclude that the measure of patented inventions provides a fairly good, although not perfect, representation of innovative activity in these five industries. Therefore, patents have been extensively used in earlier research to understand the innovation processes of firms within these industries (e.g., Katila and Shane, 2005; Coad and Rao, 2008; Rothaermel and Alexandre, 2009).

We use firm-level data on innovation and options trading from several data sources. Our starting point is the Compustat universe, which contains detailed information on all U.S. publicly listed firms since the mid-1950s. We identified all firms traded on NYSE, Amex, or Nasdaq with accounting data available between 1996 and 2004. To mitigate backfilling bias, we require firms to be listed on Compustat for three years before including them in the sample. Our main Compustat items are sales (SALE); a capital-labor ratio constructed from the net stock of property, plant, and equipment (PPENT) and the number of employees (EMP); and R&D expenditure (XRD). R&D is used to create R&D capital stocks, calculated using a perpetual inventory method with a 15% depreciation rate following the method described in Hall, Jaffe, and Trajtenberg (2005).

Firm-level patent data are obtained from the latest version of the National Bureau of Economic Research (NBER) Patent Citation database, which contains approximately three million patents granted by the United States Patent and Trademark Office (USPTO) and citation information from 1976 to the end of 2006 (Hall, Jaffe, and Trajtenberg, 2001; Jaffe and Trajtenberg, 2002).[7] We use patents that are ultimately granted, dated by the year of application, which approximates the year when the invention was completed because the patent system provides incentives to file quickly. To match Compustat firms with U.S. patent assignee codes, we begin with the name-matching tool of Bessen (2009) and then search by hand for variations on the names in our panel. Our sample ends in 2004 because many patent applications filed in the later years (i.e., 2005 and 2006) might still be under revision (Hall, Jaffe, and Trajtenberg, 2001).

For data on options trading, we use OptionMetrics. This database contains information on the daily number of contracts traded for each individual put and call option on U.S. publicly listed equities, along with daily closing bid and ask prices from 1996 onwards. The sample is selected to include firms with positive options volume to maintain comparability, as firms without options listings tend to be small (Mayhew and Mihov, 2004) with different structural relationships between innovation and the right-hand variables.[8] To approximate the total annual dollar options volume, we use the approach in Roll, Schwartz, and Subrahmanyam (2009). Specifically, for each stock, we first multiply the total trade in each option by the end-of-day quote midpoint for that option and then aggregate this number annually across all trading days and all options listed on the stock.

[6]Strictly speaking, patents are inventions. As Freeman and Soete (1997, p. 22) note, they represent "[...] an idea, a sketch or a model for a new improved device, product, process or system. Such inventions may often (not always) be patented but they do not necessarily lead to technical innovations."

[7]See https://sites.google.com/site/patentdataproject.

[8]For example, Acs and Audretsch (1988) show that small firms spend disproportionately less on R&D, but they appear to benefit more from R&D investments, suggesting they are more efficient at R&D than their larger counterparts.

To calculate other control variables and the variables used for exploring underlying mechanisms, we collect institutional ownership information from Thomson Reuters' CDA/Spectrum Institutional Holdings data set (SEC Form 13F), corporate governance information from the RiskMetrics database, analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S) database, CEO age and compensation from ExecuComp, stock price information from the Center for Research in Security Prices (CRSP), intraday trades and quotes for constructing stock illiquidity measures from the Trade and Quote (TAQ) database, and information on each firm's alliances and joint ventures from the Securities Data Company (SDC) Platinum database.

These data sets do not overlap perfectly; thus, our baseline regressions run from 1996, the first year for which options trading data are available, to 2004, the last year when we can realistically construct innovation measures based on patent data. Although the exact number of observations depends on the specific regression, the baseline sample for which we estimate the equations contains 3,271 observations of 548 firms.[9]

2.3.1 Dependent variables

Our primary measure of innovation is a *future* citation-weighted count of U.S. patents. We prefer patents weighted by citations as an indicator of innovative "output" over simple counts because patent citations can better reflect the technological and economic "importance" or "value" of the underlying invention (Trajtenberg, 1990; Albert, Avery, Narin, and McAllister, 1991). Specifically, the use of patent citations exploits the fact that patent applications must acknowledge "prior art," in which light they need to meet the requirements for patentability, i.e., U.S. patent law requires an invention to be novel, non-trivial, and susceptible to industrial application for a patent to be granted (35 U.S. Code §102).[10] These citations serve an important legal function because they can delimit the scope of the property rights awarded to the inventor. U.S. patent applicants are legally required to disclose any knowledge upon which their inventions are based. This prior art is typically referenced through citations provided by patent applicants (inventors or their lawyers) and patent examiners. Because of this important legal function, the economics of innovation literature has frequently used the number of forward citations received by a patent as an indirect measure of its value (e.g., Pakes and Griliches, 1980; Harhoff, Narin, Scherer, and Vopel, 1999; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Hall, Jaffe, and Trajtenberg, 2005; Aghion, Van Reenen, and Zingales, 2013). To control for the fact that citation counts are inherently truncated, we employ three strategies. First, we estimate until 2004, allowing for a two-year window of forward citations for the last cohort of patents in the data. Second, we include a full set of time dummies, which accounts for the fact that patents taken out later in the panel have less time to be cited than patents taken out earlier in the panel.

[9] Our sample faces another restriction from the overall Compustat database. Because our preferred regressions use firm fixed effects, we condition our sample on firms that received at least one citation and had at least two years of non-missing data for all variables between 1996 and 2004. Thus, we drop firms from the Compustat/USPTO match that patented prior to 1996 but not in the 1996–2004 period, and of those that did patent, we drop those that did not receive citations.

[10] See https://www.uspto.gov/web/offices/pac/mpep/mpep-9015-appx-l.html.

Third, we also perform our estimations using simple unweighted patent counts.[11]

We consider several additional innovation metrics. First, we use R&D expenditure as a measure of innovation inputs. Because more than 50% of firms in the entire Compustat database do not report R&D expenditures, we follow common practice in the literature by replacing missing values with zeros, although we obtain similar results when we drop these observations or interpolate over any gaps of three years or less.[12] Second, given that self-citations may differ from other citations in various ways (Hall, Jaffe, and Trajtenberg, 2005), we weight patents by the number of non-self forward citations. Finally, in a series of extensions, we examine changes in the direction of innovative efforts. To proxy for the direction of a firm's activities in its innovative process, we use the diversity of activities (i.e., the dispersion of the firm's patent portfolio across technological classes), originality-weighted patent counts (i.e., the dispersion of backward citations across technological classes), and a measure of risk-taking (i.e., the standard deviation of forward citations across patents).

It is important to note, however, that using patent data to measure innovation also has limitations. In particular, not all firms patent their inventions because some inventions do not meet the patentability criteria, and others are not patented for strategic reasons. Moreover, firms differ in their patenting propensity, and the degree to which these factors are problematic varies substantially across industries (e.g., Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches, 1987; Cohen and Levin, 1989; Griliches, 1990). We believe that limiting our study to specific industries in which patents are a meaningful indicator of technological activities reduces such concerns because other factors that may affect patent propensity are relatively stable within such a context (Cohen and Levin, 1989; Griliches, 1990). Because firms may differ in their patenting propensity for unobserved reasons even in R&D-intensive industries, we treat this problem as one of unobserved heterogeneity across industries and firms and control for such variations in our statistical analysis.[13]

2.3.2 Descriptive statistics

Table 2.1 provides summary statistics of the main variables used in this study.[14] Our sample firms are large: $494 million in net sales at the median and 2,400 employees. On average, a firm in our sample has 62 granted patents per year and subsequently receives 294 citations for its

[11] We also experimented with adjusted citations, taking into account systematic differences in the number of citations each patent receives across application year and technological class (Hall, Jaffe, and Trajtenberg, 2001). This delivers very similar results to the unadjusted citation results presented here.

[12] Note that the fact that a firm does not report R&D expenditures in its financial statement does not necessarily imply that the firm is not engaging in R&D. Because this information is public, a firm could decline to report for strategic reasons.

[13] For example, one concern might be that our analysis includes firms in "complex" (i.e., SIC codes 35, 36, 37, and 38) and "discrete" industries (i.e., pharmaceuticals; SIC code 283) in the sense proposed by Cohen, Nelson, and Walsh (2000). The authors define complex (discrete) industries as those in which a given technology is protected by many (few) patents. One might therefore observe a lower number of patents generated by firms in discrete industries, but this does not necessarily imply that these firms are less innovative. Moreover, one may argue that our industry classification is too broad to isolate, for example, the role of highly innovative biotechnology companies within the pharmaceutical industry. We account for this potential bias in our regressions by using the most detailed industry classification available (i.e., four-digit SIC code).

[14] Descriptive statistics for all other variables used throughout the course of our study are in the Appendix, Table A.16.

patents, which is comparable to previous studies (e.g., Aghion, Van Reenen, and Zingales, 2013). The citation series is highly skewed, with a median of 15. Due to the right-skewed distribution of cite-weighted patents, we use the natural logarithm as the main innovation measure in our analysis. To avoid losing firm-year observations, we add one to the actual values when calculating the natural logarithm. The options volume measure has a mean value of $157 million and a median value of $8.5 million. Regarding the other variables, an average firm invests $287 million in R&D, approximately 51% of shareholders are institutional investors, the average firm's return on assets is 9%, and 22.5 years have passed since its inclusion in Compustat.

Table 2.1
Descriptive statistics

	Mean	StdDev	Min	Median	Max	Observations	Source
Cite-weighted patents	294	1,181	0	15	18,950	3,271	USPTO
Patents	62.4	185	0	7	2,355	3,271	USPTO
Non-self cite-weighted patents	233	906	0	12	17,188	3,271	USPTO
Originality-weighted patents	30.8	89.3	0	4.0	1,158	3,245	USPTO
Std. dev. of patent citations	4.9	6.0	0	2.8	66.5	2,382	USPTO
Innovative diversity	0.62	0.21	0	0.67	0.94	1,526	USPTO
Options volume (in $m)	157	700	0.0002	8.5	15,135	3,271	OptionMetrics
Moneyness	0.29	0.17	0.06	0.25	2.4	3,271	OptionMetrics
Institutional ownership (in %)	50.7	27.5	0	56.8	100	3,271	CDA/Spectrum 13F
Fixed capital (in $m)	1,013	3,913	0.04	105	84,101	3,271	Compustat
Employees (in 000s)	15.2	34.8	0.01	2.4	372	3,271	Compustat
Sales (in $m)	3,968	11,841	0.004	494	171,652	3,271	Compustat
Firm age	22.5	15.5	3	16	55	3,271	Compustat
R&D (in $m)	287	811	0	39.4	12,183	3,271	Compustat
1 - Lerner index	0.86	0.04	0.76	0.87	0.96	3,271	Compustat
Profits/Assets	0.09	0.17	-1.4	0.12	0.62	3,271	Compustat
CEO age	55.6	7.6	32	56	89	1,996	ExecuComp
CEO vega (in $000s)	158	292	0	73.7	4,578	1,845	ExecuComp
CEO delta (in $000s)	762	1,695	0	295	34,647	1,845	ExecuComp
Governance index	9.0	2.7	2	9	16	921	RiskMetrics and Gompers et al. (2003)

As a preamble to our main analysis, we provide the results of non-parametric regressions that consider the relationship between our innovation measures and options trading. Fig. 2.1 presents the results. In both panels, we show a line for the local linear regression estimated by the lowest smoother with a bandwidth of 0.8. Panel A displays the non-parametric relationship between the natural logarithm of (one plus) the number of patents granted (unweighted patent counts) and the natural logarithm of options volume. Panel B replicates the graph but uses our primary measure of innovation, the natural logarithm of (one plus) forward citation-weighted patent counts. As can be seen, the correlation between innovation and options trading is clearly positive and appears to be monotonically increasing across options volume.

Panel A. Patent counts *Panel B. Cite-weighted patent counts*

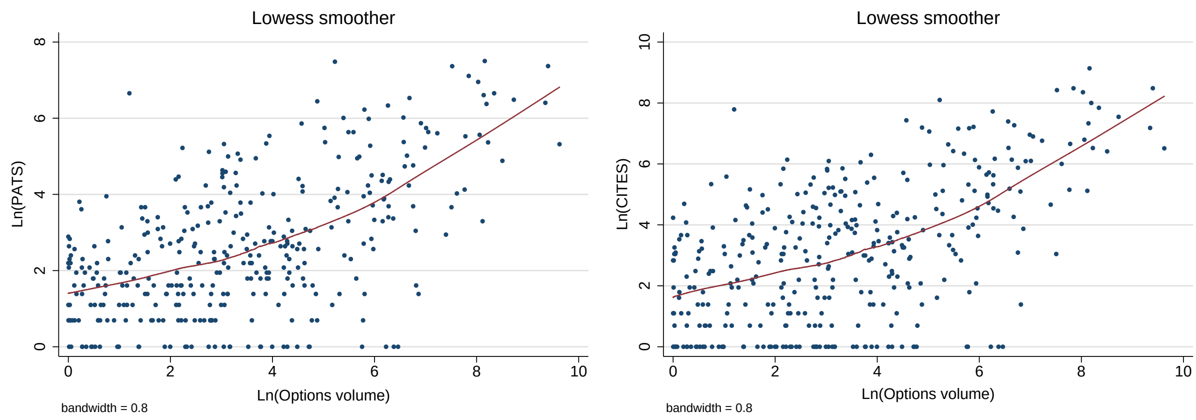

Fig. 2.1. Non-parametric regressions of innovation and options volume

2.3.3 Specification

Our main econometric models focus on the relationship between future cite-weighted measures of innovative activity and options trading. We estimate the following model using ordinary least squares (OLS):

$$Y_{i,t} = \alpha + \beta O_{i,t} + \gamma Z_{i,t} + \delta_t + \lambda_i + \varepsilon_{i,t} \tag{2.1}$$

where i indexes firms and t indexes time. The dependent variable, $Y_{i,t}$, is the natural logarithm of (one plus) the number of cite-weighted patents. The options trading measure, $O_{i,t}$, is measured for firm i over its fiscal year t as the logarithmic transformation of the options volume, although similar results are also obtained using the untransformed variable. Because both innovation and options activity are in logarithmic form, the coefficient on O gives us the elasticity of innovation to options trading. δ_t are time dummies that account for intertemporal variation that may affect the relationship between options trading and innovation and λ_i is a firm fixed effect that controls for unobserved time-invariant firm heterogeneity. Because innovation metrics are likely to be autocorrelated over time, all of our models will allow the standard errors to have arbitrary heteroskedasticity and autocorrelation (i.e., clustering standard errors by firm). The vector $Z_{i,t}$ contains a range of control variables. Specifically, in our main regressions, we condition on firm size (*Sales*), capital-labor ratio (K/L), and deflated *R&D stock*, as suggested by the literature on patent production functions (e.g., Pakes and Griliches, 1980; Hausman, Hall, and Griliches, 1984). The model of Aghion, Van Reenen, and Zingales (2013) shows that innovative activities are affected by institutional ownership; we include the percentage of shares held by institutional investors (*InstOwn*). We also control for a firm's *Age* in the baseline model, measured as the number of years since the inclusion of the firm in Compustat.

When a firm's *R&D stock* is included in Z, we can interpret the equation as a "production function" that relates past R&D investments to innovative outputs. It follows that in this specification, β gives us the effect of options trading activity on the productivity of R&D, measured by forward cite-weighted patent counts per R&D dollar invested. Note that we also estimate models that omit the R&D stock from Z, and hence, β indicates the combined impact of changes in R&D stocks and innovative productivity.

Finally, λ_i, the fixed effects term, is introduced into the models using the "pre-sample mean scaling" estimator of Blundell, Griffith, and Van Reenen (1999). Essentially, we exploit the fact that we have a long pre-sample history of a firm's innovative activities and construct pre-sample averages of the dependent variables.[15] This initial condition can proxy for unobserved heterogeneity if the first moments of the variables are stationary. Monte Carlo simulations show that this pre-sample mean scaling estimator performs well compared to alternative econometric estimators for dynamic panel data models with a long panel for innovations but only a short panel for the explanatory regressors.

2.4 Empirical results

Table 2.2 presents our first set of regression results. Columns 1 through 4 report the OLS estimates with the dependent variable *Ln(1+CITES)*: the natural logarithm of (one plus) the number of citation-weighted patents for issued patents applied for in year t. Due to the count-based nature of citation and patent data, we also use count-based regression models, such as the Negative Binomial (NB). Columns 5 through 8 report NB regressions. Across all the columns of Table 2.2, the coefficient estimates on *Ln(Optvol)* are positive (ranging between 0.118 and 0.244) and both economically and statistically significant. For example, the coefficient of 0.118 in column 4 suggests that a 200% increase in the dollar volume of options traded (e.g., from the median of \$8.5 million to \$25.5 million) is associated with a 24% increase in cite-weighted patents (e.g., from the median of 15 to 19).[16]

We begin in column 1 with OLS regressions of *Ln(1+CITES)* on options trading with controls for *InstOwn*, *Ln(K/L)*, *Ln(Sales)*, *Ln(Age)*, four-digit industry dummies, and time dummies. Consistent with the bivariate relationships in Fig. 2.1, there is a positive and significant association between innovation and options volume. Column 2 includes the controls for fixed effects (which are highly significant), and these substantially reduce the coefficient on *Ln(Optvol)* from 0.232 to 0.148. In columns 1 and 2, the options volume coefficient measures the combined impact of changes in R&D productivity (more innovative output per dollar of R&D invested) and innovative intensity (greater spending on innovation). In column 3, we add the natural logarithm of each firm's deflated R&D stock, and hence the equation becomes a production function, where β indicates the innovative premium of options trading per dollar of R&D. As expected, the coefficient on *Ln(R&D stock)* shows a very robust positive association with patent citations. The coefficient on options volume also declines by approximately 32%, from 0.232 to 0.158, indicating that the main effect of options trading operates by impacting R&D productivity rather than by stimulating more R&D spending. Column 4 presents the full model, which includes the controls for fixed effects. As before, this reduces the options volume coefficient from

[15] We estimate from 1996 and use the information on patenting between 1976 and 1995 to construct the pre-sample means.

[16] In the sample period between 1996 and 2004, the trading volume for our firms rose by 188%, and thus 200% is a reasonable change to consider.

0.158 to 0.118.[17] The final four columns of Table 2.2 repeat the main OLS specifications but use NB models. Our findings are similar.

Table 2.2
Options volume and innovation

Method	OLS				NB			
Dependent Var.	Ln(1+CITES)				CITES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Optvol)	0.232***	0.148***	0.158***	0.118***	0.244***	0.157***	0.163***	0.121***
	(0.027)	(0.022)	(0.025)	(0.022)	(0.026)	(0.022)	(0.026)	(0.021)
InstOwn	-0.229	-0.139	-0.046	-0.048	-0.211	-0.127	0.093	0.064
	(0.200)	(0.165)	(0.178)	(0.158)	(0.228)	(0.188)	(0.206)	(0.177)
Ln(K/L)	0.065	-0.004	0.102*	0.026	0.224**	0.075	0.260***	0.110
	(0.070)	(0.056)	(0.061)	(0.053)	(0.097)	(0.074)	(0.083)	(0.067)
Ln(Sales)	0.395***	0.266***	0.141***	0.140***	0.399***	0.293***	0.159***	0.142***
	(0.046)	(0.036)	(0.053)	(0.041)	(0.044)	(0.035)	(0.048)	(0.040)
Ln(Age)	0.115	-0.037	-0.051	-0.109	-0.062	-0.136	-0.266***	-0.213**
	(0.106)	(0.087)	(0.096)	(0.083)	(0.109)	(0.098)	(0.101)	(0.094)
Ln(R&D stock)			0.462***	0.262***			0.486***	0.302***
			(0.058)	(0.046)			(0.047)	(0.042)
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,271	3,271	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS and NB panel regressions of firms' patents weighted by the number of forward citations (*CITES*) on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. The time period is 1996 – 2004 (with citations up to 2006); fixed effects are based on including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.4.1 Alternative innovation measures

In Table 2.3, we ask whether our results are driven by greater innovation output (more patents) or greater innovation input (more R&D expenditure) and whether our results are robust to the exclusion of self-citations. We find support for all three effects.

Columns 1 and 2 report the regression results from replacing the dependent variable of cite-weighted patents with raw patent counts. We observe a pattern for the coefficient of options trading activity that is very similar to that in our baseline models (i.e., columns 3 and 4 of Table 2.2). We observe a positive and significant coefficient estimate of *Ln(Optvol)* that declines substantially after we introduce time-invariant, firm-specific innovation determinants into the regressions. The effect, however, remains economically and statistically significant. For example, the coefficient estimate in column 2 implies that an increase in options volume of 200% leads to roughly two additional patents filed by the median firm in our sample. Given that the median firm files for seven patents, this is a significant increase.

The middle two columns examine the association between options trading activity and R&D investment. We remove the deflated *R&D stock* from this specification because we are interested in inputs and rely instead on a conditional fixed-effects estimator. In columns 3 and 4, we

[17] The results are similar if we replace the Blundell, Griffith, and Van Reenen (1999) controls for fixed effects with the Hausman, Hall, and Griliches (1984) approach. For example, in an identical specification to our main model in column 4, the coefficient (standard error) on *Ln(Optvol)* is 0.091 (0.034).

find that options volume has a significant and positive association with firm R&D investment, although the magnitude of this effect becomes smaller than that for cite-weighted patents after we add fixed effects. Thus, focusing on R&D as the only measure of firm innovativeness may underestimate the importance of options trading.

Columns 5 and 6 of Table 2.3 show that the coefficient estimates on *Ln(Optvol)* continue to be positive and significant at the 1% level when we remove self-citations and re-estimate Eq. (2.1) with the dependent variable replaced by the number of patents weighted by non-self citations. We find this last result important because the interpretation that our results are driven primarily by pure managerial signaling behavior (as opposed to pushing the firm toward more innovation) is difficult to reconcile with our finding that firms with higher levels of options trading activity generate more forward citations in general and receive more forward citations from other firms in particular (e.g., compared with an increase in patenting).

Table 2.3
Options volume and alternative innovation measures

Dependent Var.	Ln(1+PATS)		Ln(1+XRD)		Ln(1+NS_CITES)	
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.176***	0.158***	0.268***	0.102***	0.198***	0.157***
	(0.029)	(0.024)	(0.029)	(0.014)	(0.032)	(0.028)
InstOwn	-0.273*	-0.213	-0.283*	0.017	-0.025	-0.045
	(0.154)	(0.140)	(0.162)	(0.102)	(0.167)	(0.149)
Ln(K/L)	0.101**	0.043	-0.060	0.080**	0.094*	0.032
	(0.051)	(0.044)	(0.062)	(0.031)	(0.056)	(0.052)
Ln(Sales)	0.144***	0.118***	0.516***	0.240***	0.133***	0.130***
	(0.046)	(0.033)	(0.041)	(0.034)	(0.049)	(0.039)
Ln(Age)	0.010	-0.028	0.087	0.605***	-0.022	-0.094
	(0.079)	(0.069)	(0.078)	(0.151)	(0.091)	(0.080)
Ln(R&D stock)	0.432***	0.205***			0.431***	0.255***
	(0.056)	(0.043)			(0.056)	(0.045)
SIC four-digit dummies	Yes	Yes	Yes	n/a	Yes	Yes
Firm fixed effects	No	BGV	No	Yes	No	BGV
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS regressions of firms' unweighted patent counts (*PATS*), R&D expenditure *(XRD)*, and patents weighted by the number of non-self forward citations *(NS_CITES)* on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of time dummies. The time period is 1996 – 2004 (with non-self citations up to 2006); *BGV* fixed effects controls use the Blundell, Griffith, and Van Reenen (1999) pre-sample mean scaling estimator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.4.2 Robustness checks

We conduct a rich set of basic robustness tests for our baseline results and discuss the details of these tests in the Appendix. To summarize, we find that the positive effect of options trading activity on innovation continues to increase monotonically, is preserved in the two subperiods during and after the Internet bubble, is robust to alternative proxies for R&D inputs, lagged options volume, and alternative econometric models that address the right-skewed and non-negative nature of patent data.

To provide additional insights, we conduct several tests related to our main prediction. To save space, these results are tabulated in the Appendix. First, we assess whether our results are robust to the inclusion of additional (financial) control variables. Although our approach is to condition on a wide range of firm characteristics (and fixed effects), one could object that this does not adequately control for observable omitted variables. For example, there may be concerns that our regressions omit the variable of a firm's market value, which is correlated with the number of citations (Hall, Jaffe, and Trajtenberg, 2005). Given that fundamentals that increase a firm's value may also increase innovation and because informed traders may be more likely to trade firms with higher growth opportunities, this may produce a spurious upward bias in the coefficient on options volume.[18] Similarly, He and Tian (2013) and Fang, Tian, and Tice (2014) show that analyst coverage and stock liquidity are important determinants of firm innovation. To address such concerns, in the Appendix, Table A.8, we augment our main specification by including stock illiquidity (*Illiquidity*), leverage (*Leverage*), stock market-based firm value (*Tobin's Q*), return on assets (*ROA*), capital expenditures (*Capex*), and analyst coverage (*Analyst coverage*). However, the coefficients on *Ln(Optvol)* continue to be positive and significant at the 1% level, and the magnitude of the coefficient declines only slightly from the baseline model (i.e., from 0.118 to 0.110).[19]

Another concern might be that our results are affected by firms' external knowledge-sourcing behavior. Because of the increased complexity of the technological and scientific developments in our focal industries, firms cannot rely solely on internal R&D; they need to (and do) source knowledge externally to enhance the performance of their innovation process (Cassiman and Veugelers, 2006). Simultaneously, when prices are more efficient, managers can extract more information from the market, thereby allowing them to better assess the quality and potential outcomes of external knowledge acquisition activities.[20] To account for this, we include three alternative variables in our set of controls. Specifically, we use the *frequency* with which firms engage in R&D collaborations (i.e., the number of alliances and joint ventures reported in SDC), the *intensity* with which firms have sourced external knowledge (i.e., the number of jointly owned patents divided by the total number of patents), and the *acquisition* of innovative target firms (i.e., acquisition expenditure normalized by total assets). We report the results in the Appendix, Table A.9. We find that the coefficients on *Ln(Optvol)* continue to be of a very similar magnitude to those in column 4 of Table 2.2 (except when controlling for collaboration frequency because we only consider firms that have some information in SDC) and continue to be significant at the 1% level. Overall, this serves as reassurance that our findings are primarily related to internal R&D investment decisions.

Third, we argue that information asymmetries between the firm and market participants

[18] The correlation between *Tobin's Q* and *Ln(Optvol)* is positive (0.262) and significant at the 1% level.

[19] In unreported results, we also consider return volatility, measured by the annualized standard deviation of daily returns. However, and consistent with the notion in Roll, Schwartz, and Subrahmanyam (2009), the return volatility variable is not significant. For example, in an identical specification to column 1 in Table A.8 in the Appendix, the coefficient (standard error) on return volatility is 0.017 (0.012), while the coefficient on *Ln(Optvol)* remains positive and significant at the 1% level, with the magnitude of the estimate almost identical to that reported above.

[20] Prior studies provide evidence consistent with this argument. For example, Luo (2005) finds that the positive correlation between announcement date return and the completion of mergers can be attributed to insiders' learning from outsiders after controlling for common information.

are especially challenging in R&D-intensive industries (which is one reason that this is our sample of interest). This is because the nature of firms' core activities is knowledge-based and highly opaque, and the fact that there could be a substantial cost of revealing information to their competitors reduces the quality of the signal they can send about their innovative activities (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). Thus, if what we are capturing is related to the informational benefit from options to a firm in reducing asymmetric information problems related to R&D, then this should be more important for firms that are active in R&D-intensive industries, relative to cases in which such problems are less (or not at all) present. To reveal this, we begin by identifying firms with positive options volume and non-missing data on all other variables that operate in non-R&D-intensive industries, defined as those that are located in the OECD classification (based on R&D intensities) of low-tech industries (Organisation for Economic Co-operation and Development, 2011).[21] As these firms are very different from our focal firms, we then apply a matching procedure that relies on a nearest-neighbor matching of propensity scores (estimated as a function of all firm characteristics, including fixed effects). After restricting the sample to the common support, we are left with a panel of 1,453 firm-years in both groups. In column 1 of Table A.10 in the Appendix, we estimate our main specification on the matched sample, adding a dummy variable for R&D-intensive firms (= 1;0 = non-R&D-intensive). The coefficient on *Ln(Optvol)* remains positive (0.120) and statistically significant at the 1% level, while the coefficient on the dummy is also positive (1.219) and significant at the 5% level. In column 2, we add the interaction of this dummy variable with options volume. The estimates show that the interaction term, *Ln(Optvol) x Dummy for high-tech*, is 0.186 and highly significant, as expected. Most interesting, however, the coefficient on *Ln(Optvol)* goes toward zero (0.004) and becomes insignificant once the interaction term is included. Taken literally, this indicates that there is no effect of options trading activity on innovation in non-R&D-intensive industries, which is broadly consistent with the story we present. For robustness, we also split the sample. In column 3, in R&D-intensive industries, the coefficient on options volume is large, positive, and significant at the 1% level, whereas in column 4, in non-R&D-intensive industries, the coefficient is smaller and insignificant (0.144 versus 0.070).[22]

Finally, we perform a small event study that examines the effect of initial option listings on firms' innovation performance. To do so, we focus on the subsample of firms that appear for at least two years before and after the listing event. After excluding firms with multiple listings,

[21] According to industrial codes of the International Standard Industrial Classification of All Economic Activities (ISIC Rev.3), the Organisation for Economic Co-operation and Development (2011) classifies manufacturing industries into four subgroups, high-technology, medium high-technology, medium low-technology, and low-technology, based on the technology intensity and level of R&D used in these industries.

[22] Clearly, as detailed in Section 2.3, this approach has the problem that patent and citation data are a less reliable indicator of innovation in low-tech industries. To address this, we experimented with different subsamples of non-R&D-intensive firms such as including low- and/or medium low-tech industries and focusing only on those firms that have nonzero citations in more than 25% or 50% of the years they appear in our sample. Our finding, however, remains unaltered in all these tests. For example, re-performing the analysis using a matched sample of firms in low-tech industries that receive citations in more than 50% of the years yields the following results: we estimate a coefficient on the interaction term of 0.240 (standard error = 0.061) and a coefficient on options volume of -0.054 (standard error = 0.052) on this subsample of 2,192 observations. If we split this subsample into R&D- and non-R&D-intensive industries, the coefficient on *Ln(Optvol)* is large and significant only for firms in R&D-intensive industries (i.e., a coefficient of 0.130 with a standard error of 0.053 versus a coefficient of 0.023 with a standard error of 0.056).

we are left with a set of 93 events during the period between 1998 and 2002. Next, we proceed to construct a dummy variable, *Post*, that equals one for the post-event period and zero for the pre-event period. In column 1 of Table A.11 in the Appendix, we augment Eq. (2.1) by including *Post*. The within-firm estimator is 0.370 and significant at the 5% level. In terms of economic significance, this suggests that option listing is associated with a 37% increase in patent citations in subsequent periods. In our second diagnostic test, we examine the dynamics of innovation in the years around the listing event. We use a window of eight years and include in our main specification a set of dummy variables for the three years prior to the year when the firm was listed and four years after the firm was listed (year zero is the omitted category). Fig. 2.2 presents the results. Panel A depicts the coefficient estimates on the relative year dummies for the raw number of patents and Panel B shows them for cite-weighted patents. In both figures, we find that there is little effect in the first year after listing, but in the following years the point estimates increase substantially in magnitude with respect to the listing year.

Two conclusions emerge from this analysis. First, it mitigates concerns that options trading is endogenous due to reverse causality. This is a particular concern when studying innovation output because it is difficult to address by lagging the explanatory variable. Even if innovation is regressed on lagged options volume (as is done in the Appendix, Table A.3), it may be that lagged innovation causes lagged options volume and also causes current innovation. Because we only consider the first listing (based on the data available to us), it cannot be caused by past listings. Second, the phenomenon of such delayed effects is consistent with the starting point of our theory, i.e., that the benefit from options is related to whether the market for the listed option has sufficient volume because trading volume requires time to build.

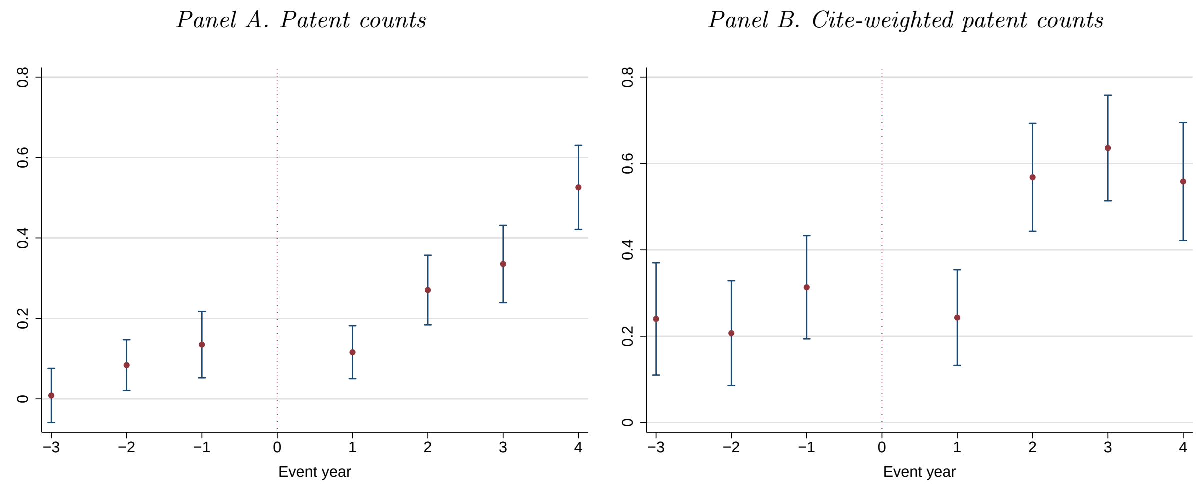

Fig. 2.2. Initial option listing and innovation

2.4.3 Innovative direction

We now employ alternative outcome variables to explore the idea that our baseline results are not simply driven by greater R&D productivity (more citations per R&D dollar) but are rather associated with different resource allocation decisions (or innovative directions). To perform such a test, we use three different measures of the direction of firms' innovative efforts: (i) an originality index regarding knowledge inputs, (ii) a measure of risk-taking behavior, and (iii) a proxy for innovative diversity. The results are reported in Table 2.4. As before, all models are estimated via fixed effects OLS panel regression using the pre-sample mean of the dependent variables. We lose some observations in these specifications because in the fixed effects estimator, we require a firm to have at least some information on the dependent variables in the 1996 – 2004 and pre-sample periods.

In column 1, the outcome variable is an originality-weighted patent count. Originality, as defined in Hall, Jaffe, and Trajtenberg (2001), is essentially one minus a Herfindahl index of the concentration of backward patent citations across two-digit technological classes. We find that the coefficient estimate on *Ln(Optvol)* is positive and significant at the 1% level, suggesting that firms with more options trading activity make use of a more diverse set of knowledge.[23] In the next column, we use a measure of risk-taking behavior, i.e., the standard deviation of forward citations received across patents. The results show that there is a positive and meaningful relationship between *Ln(Optvol)* and *Ln(1+SD_CITES)*.[24] In column 3, we introduce the diversity of innovation activities, defined as one minus the Herfindahl index of the number of patents across classes. The patent portfolio includes all patents of a given firm over a three-year period. To control for the fact that some firms are engaged in so little innovation that it may not be meaningful to speak of a diverse (or concentrated) technological direction, we define a minimum threshold of five patents to filter out such low-innovation firms.[25] As shown, the estimate on *Ln(Optvol)* is positive and significant at the 10% level, suggesting that firms with more options trading activity file for a more diverse set of patents.[26]

Taken together, the results in Table 2.4 reveal that options trading appears to evoke a change in the direction of innovative efforts and not merely increase the amount of R&D or patenting; on average, firms with more trading activity produce a more diverse and original set of activities and are characterized by an increasing willingness to take risk in their innovation process. We find these results especially intriguing because, intuitively, one may conjecture that the disciplinary feature of financial markets is to force managers to refrain from engaging in overly risky projects and to abandon creativity and diversity for efficiency purposes. We take these results as a starting point to explore the question of why this is the case in Section 2.5.

[23] The coefficient on options volume continues to be positive and significant when we use NB (coefficient of 0.157 with a standard error of 0.024) and Poisson (coefficient of 0.114 with a standard error of 0.050) specifications.

[24] Our findings are similar if we use the untransformed variable: the coefficient (standard error) on *Ln(Optvol)* is 0.319 (0.085) in column 2 of Table 2.4 when *Ln(1+SD_CITES)* is replaced by *SD_CITES*.

[25] We also consider alternate cut-off points of ten, 20, and 50 patents and obtain similar results.

[26] For robustness purposes, we apply an alternative modeling approach that accounts for the bounded nature of the dependent variable. Specifically, we employ a double-truncated Tobit model and find similar results for the coefficient on options trading (i.e., the coefficient is 0.008 with a standard error of 0.004).

Table 2.4
Options volume and innovative direction

Dependent Var.	Ln(1+ORIG.)	Ln(1+SD_CITES)	DIVERSITY
Method: OLS	(1)	(2)	(3)
Ln(Optvol)	0.154***	0.039***	0.007*
	(0.022)	(0.010)	(0.004)
InstOwn	-0.140	0.104**	0.028
	(0.127)	(0.052)	(0.023)
Ln(K/L)	0.032	-0.022	0.005
	(0.037)	(0.024)	(0.010)
Ln(Sales)	0.086***	0.010	0.027***
	(0.030)	(0.012)	(0.007)
Ln(Age)	-0.026	-0.082***	0.018
	(0.060)	(0.029)	(0.013)
Ln(R&D stock)	0.159***	0.041***	-0.003
	(0.040)	(0.012)	(0.006)
Observations	3,245	2,382	1,526

This table presents estimates of OLS panel regressions of firms' patents weighted by originality (*ORIG.*), the standard deviation of forward citations across firms' patents (*SD_CITES*), and innovative diversity *(DIVERSITY)* on options volume (*Optvol*) and other firm-level control variables. See Hall, Jaffe, and Trajtenberg (2001) for a definition of originality. Diversity is defined as one minus the Herfindahl index of the number of patents across two-digit technological classes. Firms in columns: 542 in column 1, 455 in column 2, and 362 in column 3. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.4.4 Endogeneity of options trading

In this subsection, we address concerns that informed traders select firms on the basis of characteristics that are observable to the traders but not observable for us. For example, informed investors might decide to trade options on stocks when they anticipate an increase in innovation. Another problem might be that our measure of options trading activity is noisy. This is because intraday execution prices are not available over the long sample period. Although this is mitigated by annual averaging, we are likely to underestimate the effect of options.[27]

We address these issues in a number of ways. First, we use matching estimators to calculate the average effect of having high levels of options volume on innovation. Second, we consider moneyness and open interest as two plausible exogenous instrumental variables and perform 2SLS estimations of the regressions in Table 2.2. Third, we test in Section 2.5 whether our results are consistent with additional predictions and empirical findings concerning the environment in

[27] Another issue might be that different types of options provide different signals. Although we could employ additional data to examine the breakdown of call and put options with different times to maturity, there are no clear hypotheses. As Roll, Schwartz, and Subrahmanyam (2009) note, while it may be the case that managers are more likely to act on "good news" than on "bad news," calls and puts can be bought and sold freely. Thus, in the absence of information on the signed order imbalance (data we unfortunately lack), disaggregating calls and puts cannot be unambiguously linked to managerial investment decisions.

which options trading should have differential effects on innovation.[28]

Propensity score matching

We begin with propensity score matching (PSM) to determine whether firms with high trading activity would have innovated at a lower rate had they not had high trading activity. In the application that follows, we define a high (low) trading activity firm as a firm with options volume above (below) the yearly median in a given three-digit SIC industry. The PSM technique is based on the likelihood that an observation would be a high trading activity firm conditional on observables (Rosenbaum and Rubin, 1983, 1984). We use a probit specification to estimate the probabilities of being a high trading activity firm (= 1;0 = otherwise) on a comprehensive list of observable characteristics, including all the independent variables (including the additional controls), as well as fixed effects. We then use the predicted probabilities, or propensity scores (stratified by industry and year), from this probit estimation and perform the matching. As our main matching procedure, we use nearest-neighbor matching that allows each treated firm to be matched with multiple controls (i.e., four, although our results are robust to any number of matches between one and five), running the procedure with replacement. However, to ensure that the results are not sensitive to our choice of matching estimator, we also provide evidence from kernel and radius matching.

Table 2.5 reports the average treatment effect estimates. The average selection bias (not tabulated) across all specifications ranges from 3.4% to 4.7%, which means that the results are reliable. Our findings are in line with those obtained in the previous panel regressions. For example, the results in columns 1 and 2 suggest that firms with high trading activity produce 70% more patents that subsequently generate 72% more citations per dollar of R&D than firms with low options volume, all significant at the 1% level. Overall, this suggests that the non-random assignment of high levels of options trading to more innovative firms (at least based on observables) does not explain our findings.

[28] An interesting context for the purpose of our study would be the use of a difference-in-differences estimator that relies on the exogenous variation in options trading generated by short selling bans or constraints imposed by regulators during the 2007 – 2009 crisis. Unfortunately, we lack data on patenting during and after the crisis period.

Table 2.5
Options volume and innovation–Propensity score matching

	Panel A: Nearest-neighbor matching		*Panel B: Kernel matching*		*Panel C: Radius matching*	
	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)
	(1)	(2)	(3)	(4)	(5)	(6)
High Optvol vs. Low Optvol	0.722***	0.704***	0.468***	0.382***	1.155***	1.096***
	(0.104)	(0.092)	(0.125)	(0.094)	(0.072)	(0.063)
Observations	2,130	2,130	2,130	2,130	2,130	2,130

This table presents estimates of differences in firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) between the treatment group (high levels of options volume) and the control group (low levels of options volume). The matched sample is constructed using nearest-neighbor (Panel A), kernel (Panel B), and radius (Panel C) score matching with scores given by a probit model in which the dependent variable is a dummy variable that equals one if a firm has an options volume above the yearly median in a given three-digit industry. The propensity score is estimated using the following firm characteristics: *InstOwn*, *Ln(K/L)*, *Ln(Sales)*, *Ln(Age)*, *Ln(R&D stock)*, *Illiquidity*, *Leverage*, *Tobin's Q*, *ROA*, *Capex*, *Ln(Analyst coverage)*, and fixed effects. Firms in columns: 525. Standard errors are obtained using 200 bootstrap replications (in parentheses). The time period is 1996 – 2004 (with citations up to 2006).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Instrumental variable

Our second approach to correct for the potential bias due to selection is an instrumental variable strategy. Roll, Schwartz, and Subrahmanyam (2009) propose two instrumental variables that are reasonably exogenous to the relationship between options volume and innovation: (i) moneyness (i.e., the average absolute difference between the stock's market price and the option's strike price) and (ii) open interest in the stock's listed options. We focus our analysis on moneyness, while Table A.12 in the Appendix shows that our results are similar if we use the total open interest in the stock's listed options as an alternative.

A good instrument is a variable that is correlated with options trading (this assumption can be tested) but uncorrelated with our dependent variables except through other independent variables. That is, the instrument should be a variable that can be excluded from the original list of controls without affecting the results. As Roll, Schwartz, and Subrahmanyam (2009) argue, there are several reasons that moneyness is related to options trading. First, informed traders may be more attracted to out-of-the-money (OTM) options because they offer the greatest leverage but uninformed agents may prefer in-the-money (ITM) options to avoid overly risky positions (Pan and Poteshman, 2006). Moreover, volatility traders would avoid deep ITM or OTM options, as the vega of such options is close to zero. Specifically, Chakravarty, Gulen, and Mayhew (2004) show that the trading volume by agents speculating on volatility tends to be concentrated in at-the-money (ATM) options. In sum, these arguments suggest that moneyness is related to options trading, although they do not establish an unambiguous direction. There is no reason to believe, however, that (unsigned) moneyness is linked to innovation in any intrinsic way because exchanges periodically list new options with strike prices close to the stock's market price.

As there is no strong rationale for a mechanical link between moneyness and innovation, we use the average absolute moneyness as an instrument. This variable is measured as the yearly average of the daily absolute deviation of the exercise price of each traded option from the closing price of the underlying asset.[29] The correlation of this variable with options volume is 0.326, which suggests that the instrument is indeed related to options trading, and is consistent with that reported in Roll, Schwartz, and Subrahmanyam (2009). We implement the instrumental variable estimator using 2SLS.

Column 1 of Table 2.6 presents the first stage, which regresses options volume on moneyness (and all other controls). As indicated by the simple correlation, we find that the instrument is positive and highly significant. Moreover, the first-stage F-stat for the "weak instrument rule of thumb" is strongly significant (and well above ten), which suggests that the hypothesis that the instrument can be excluded from the first-stage regressions is rejected and that the instrument is not weak. Columns 2 and 3 present the coefficient estimates for the second stage, where we control for endogeneity. Column 2 presents the results with cite-weighted patents as dependent variables. Consistent with the findings from the OLS specification, the coefficient estimate on *Ln(Optvol)* is positive and significant at the 1% level. In column 3, we find a very similar pattern using unweighted patents as the dependent variable. To provide additional support for the validity of our instrumental variable approach, we replicate the estimations of Table 2.6 using open interest as an additional instrument and rely on the Hansen J-statistic. Our instrument performs adequately in our tests (p-values = 0.93 and 0.31 in identical specifications of columns 2 and 3, respectively), indicating that we cannot reject the null hypothesis of instrument suitability.

To gauge the direction and magnitude of the bias due to the endogeneity of options trading, we can compare the OLS results from Table 2.2 with those obtained from the 2SLS regressions. Interestingly, the 2SLS coefficient estimates on *Ln(Optvol)* are considerably larger (i.e., more positive) than those of the OLS estimates, although the estimates from both approaches are in the same direction and statistically significant.[30] This OLS bias toward zero could be because options trading is measured with some error or because omitted variables simultaneously make firms innovative and more attractive to informed traders. The attitudes and beliefs of CEOs could be an example of such omitted variables. For instance, overconfident CEOs could attract more informed traders, while simultaneously, they could also be more likely to pursue innovation that results in more patents and citations (Hirshleifer, Low, and Teoh, 2012).

[29] For traded option k on stock j for day d, the absolute deviation is $|\text{Ln}(\text{Price}_{j,d}/\text{Strike}_k)|$. This is averaged over all k and d within a year t for each stock j. Options without trades are not included in the calculation of the moneyness variable. We obtain very similar results if we use volume-weighted average annual moneyness for each stock j, where each option's moneyness is weighted by the proportion of total option volume for stock j contributed by that option.

[30] For robustness, we also consider the instrumental variable estimator by using the control function approach (Blundell and Powell, 2004). The coefficient estimate (standard error) on *Ln(Optvol)* in the control function estimation was also above the ordinary Poisson estimate (see Appendix, columns 4 and 8 of Table A.1): 0.188 (0.087) for *CITES*, and 0.165 (0.065) for *PATS*.

Table 2.6
Options volume and innovation–Moneyness as instrumental variable

Method	OLS (first stage)	2SLS (second stage)	
Dependent Var.	Ln(Optvol)	Ln(1+CITES)	Ln(1+PATS)
	(1)	(2)	(3)
Ln(Optvol) *(instr.)*		0.180***	0.162***
		(0.057)	(0.062)
InstOwn	1.051***	-0.033	-0.259*
	(0.224)	(0.179)	(0.134)
Ln(K/L)	-0.365***	0.095	0.061
	(0.080)	(0.067)	(0.050)
Ln(Sales)	0.595***	0.151**	0.103**
	(0.052)	(0.063)	(0.042)
Ln(Age)	-0.322***	-0.059	-0.014
	(0.123)	(0.101)	(0.071)
Ln(R&D stock)	0.361***	0.471***	0.194***
	(0.054)	(0.071)	(0.050)
Ln(Moneyness)	1.343***		
	(0.155)		
Observations	3,271	3,271	3,271

This table presents estimates of 2SLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables, with the average absolute moneyness, *Ln(Moneyness)*, as instrumental variable. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5 Possible mechanisms

Our evidence thus far is consistent with the implication of our leading hypothesis that options trading enhances firm innovation, even after accounting for potential endogeneity concerns. In this section, we turn to the last part of our analysis and discuss potential underlying mechanisms through which this may occur. It is of course challenging to provide definite proof, and hence our tests are only suggestive.

Broadly, we suggest two possible explanations for our results. The first is that managers prefer the "quiet" life as proposed by Hart (1983), Schmidt (1997), and Bertrand and Mullainathan (2003) and that the increased price informativeness induced by options trading serves as a monitoring mechanism that forces managers to invest in innovation if they are a priori reluctant to do so. Alternatively, the positive association between options trading and innovation could also be attributable to career concerns. Most prominently, Aghion, Van Reenen, and Zingales (2013) recently extend the Holmström (1989, 1999) career concern model in the context of institutional investors (i.e., blockholders) and innovation. Based on the observation that managers concerned with their reputations in the labor market have incentives to take actions that boost current earnings and the firm's current stock price (Narayanan, 1985), the authors' findings suggest that the presence of institutional investors "protects" managers against the reputational risk associated with long-term investments in innovation. Because of their informational advantage, they have the ability to assess managerial efforts in innovation independent of potential bad profit realizations in the short run. This, in turn, provides incentives for the manager to forgo short-term profits and to invest in innovation. To the extent that the previous literature, both theoretical and empirical, argues that options increase the amount of private information conveyed by prices (e.g., Cao, 1999; Chakravarty, Gulen, and Mayhew, 2004; Pan and Poteshman, 2006; Roll, Schwartz, and Subrahmanyam, 2009; Hu, 2014), we may expect that this rationale also applies in the context of active options markets.

To understand the extent to which the aforementioned stories might explain our findings, we implement several tests concerning the environments in which options trading activity should have differential effects on innovation. First, we examine whether the effect of options trading on innovation depends on product market competition. The quiet life story suggests that the effect of options trading on innovation is weaker in highly competitive environments because stronger competition increases the threat of bankruptcy, which induces the manager to work harder to avoid liquidation and to keep his job (Hart, 1983; Schmidt, 1997). In contrast, if informed agents serve as a "shield" that protects managers, this effect should be more pronounced when the degree of product market competition is higher. This is because competition reduces the chances of success and hence increases the reputational risk faced by managers if they do so. Second, we investigate how innovation varies with options volume and managerial entrenchment. As Ferreira, Ferreira, and Raposo (2011) show, a disciplining takeover is more likely when prices are more efficient. Thus, an implication of our preceding discussion is that if managers prefer the quiet life, the beneficial effect of options should be stronger when managers are more "entrenched." Specifically, if a firm adopts a large number of takeover defenses, it might become partially insulated from the market for corporate control. In such cases, the takeover market cannot play an effective disciplinary role, and managers have greater ability to shirk. Moreover, if shareholder rights are restricted (i.e., the manager has more bargaining power against shareholders), the CEO will also be more entrenched. Third, if career concerns are the driving force behind this relationship, the effect of options trading on innovation should be stronger for younger CEOs because they are more concerned with their careers, and to boost their careers, they are likely to engage in myopic behavior. Gibbons and Murphy (1992) show that implicit incentives from career concerns are much more substantial for younger managers. Holmström (1999) notes that when managerial ability is initially unknown and managerial effort is unobservable, young managers will overwork to benefit their future careers. Thus, there should be little managerial slack for younger CEOs. As before, under the quiet life story, options trading should have less of an effect when managers are younger, while under the career concerns story, the impact of options trading on innovation should be stronger when managers are younger.

2.5.1 Product market competition

Table 2.7 presents several results related to the interaction between options volume and product market competition. To measure product market competition, we use the inverse Lerner index [as in Aghion, Bloom, Blundell, Griffith, and Howitt (2005)], defined as one minus the median gross margin across all firms in the entire Compustat database with the same three-digit industry SIC as the focal firm. Our main model allows this measure to vary over time, but we also consider its time-invariant form.

The first column reproduces our baseline results (column 4 of Table 2.2) and introduces the time-varying measure of product market competition. In this specification, the coefficient estimate on competition is positive and statistically significant (more competition yields more innovation), while the coefficient on *Ln(Optvol)* remains positive and significant.[31] Column 2 includes the interaction term between options trading and product market competition, which is positive and significant at the 1% level, as predicted by the career concerns hypothesis. In columns 3 and 4, we then replace the dependent variable with raw patent counts and repeat the analysis. We observe similar patterns for the interaction term. For robustness, columns 5 and 6 repeat the same specifications as above but restrict the inverse Lerner index to be constant over time. This yields similar results. Note that we are unable to estimate the main effect of competition in this model because the measure is collinear with industry effects.

[31] In line with Aghion, Bloom, Blundell, Griffith, and Howitt (2005), we find some evidence of an inverted U-shaped relationship between innovation and product market competition. If we include a term in the square of the inverse Lerner index, it is negative, whereas the linear term remains positive. This quadratic term is insignificant, however, with a coefficient estimate of -32.205 and a standard error of 28.076.

Table 2.7
Options volume and innovation–Product market competition

Measure of competition	Varies over time				Constant over time	
Dependent Var.	Ln(1+CITES)		Ln(1+PATS)		Ln(1+CITES)	Ln(1+PATS)
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)		2.467***		1.962***	3.334***	2.579***
x Competition		(0.469)		(0.249)	(0.284)	(0.319)
Ln(Optvol)	0.169**	0.169***	0.160**	0.160***	0.165***	0.156***
	(0.046)	(0.026)	(0.037)	(0.020)	(0.029)	(0.022)
Competition	5.834***	5.054**	6.852***	6.229***		
(1 − Lerner)	(1.248)	(2.024)	(0.649)	(1.213)		
InstOwn	-0.035	0.017	-0.212	-0.171	0.027	-0.165
	(0.229)	(0.183)	(0.224)	(0.181)	(0.182)	(0.181)
Ln(K/L)	0.026	0.041	0.042	0.053	0.047	0.058
	(0.100)	(0.080)	(0.088)	(0.071)	(0.081)	(0.071)
Ln(Sales)	0.132	0.147*	0.121	0.133**	0.151*	0.135**
	(0.093)	(0.085)	(0.069)	(0.063)	(0.086)	(0.063)
Ln(Age)	-0.107	-0.089	-0.032	-0.017	-0.077	-0.007
	(0.148)	(0.111)	(0.092)	(0.069)	(0.112)	(0.071)
Ln(R&D stock)	0.251***	0.243***	0.202***	0.195***	0.244***	0.197***
	(0.048)	(0.052)	(0.035)	(0.042)	(0.052)	(0.041)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), product market competition (*Competition*), their interaction, and other firm-level control variables. Firms in columns: 548. Robust standard errors are clustered at the three-digit industry level (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006). Product market competition is constructed as 1 − the Lerner index, where Lerner is calculated as the median gross margin from the entire Compustat database in the firm's three-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.2 Managerial entrenchment

Table 2.8 analyzes the interaction between options trading and managerial entrenchment. To measure the degree of managerial entrenchment, we use the "Governance Index" (G-Index) introduced by Gompers, Ishii, and Metrick (2003). It consists of 24 corporate governance provisions and is based on firm-level corporate governance provisions and firms' governing state corporate law statutes. We obtain this information from RiskMetrics. Because this covers S&P 1500 firms in 1998, 2000, 2002, and 2004, our sample size declines in this analysis. A higher G-Index score indicates more restrictions on shareholder rights or a greater number of anti-takeover measures.

Our evidence is consistent with the findings in Table 2.7. In line with the career concerns hypothesis (and in contrast to the quiet life hypothesis), the positive association between options trading and innovation is stronger when managers are less entrenched. Specifically, the interaction between options volume and managerial entrenchment in column 2 of Table 2.8 generates a significantly negative coefficient estimate of -0.028 (significant at 5%), while the main effect of *Ln(Optvol)* remains positive and statistically significant at the 1% level. For robustness purposes, Table A.13 in the Appendix investigates the interaction between options trading and the "Entrenchment Index" (E-Index) (Bebchuk, Cohen, and Ferrell, 2009). The findings are similar.

Table 2.8
Options volume and innovation–Managerial entrenchment

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)		-0.028**		-0.018
x G-Index		(0.014)		(0.013)
Ln(Optvol)	0.179***	0.170***	0.159***	0.154***
	(0.032)	(0.032)	(0.029)	(0.029)
G-Index	0.019	0.045	0.010	0.026
(governance index)	(0.033)	(0.033)	(0.029)	(0.028)
InstOwn	-0.067	-0.094	-0.031	-0.048
	(0.191)	(0.191)	(0.169)	(0.168)
Ln(K/L)	0.152**	0.151**	0.109*	0.109*
	(0.077)	(0.076)	(0.063)	(0.063)
Ln(Sales)	0.111**	0.109**	0.123***	0.122***
	(0.050)	(0.049)	(0.046)	(0.046)
Ln(Age)	-0.184**	-0.169*	-0.114	-0.105
	(0.092)	(0.092)	(0.085)	(0.085)
Ln(R&D stock)	0.111***	0.115***	0.103***	0.106***
	(0.031)	(0.030)	(0.027)	(0.027)
Observations	921	921	921	921

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*), managerial entrenchment (*G-Index*), their interaction, and other firm-level control variables. Firms in columns: 331. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of three-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The G-Index is an average of 24 provisions in the firm's charter (see Gompers, Ishii, and Metrick, 2003). The measure is based on data from RiskMetrics from 1998, 2000, 2002, and 2004. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.3 CEO age

Finally, we examine how a CEO's age alters the effect of options trading on innovation. To capture CEO age, we extract information from ExecuComp. As before, this database covers firms in the S&P 1500, and hence we are left with a subsample. Under the career concerns hypothesis, we expect that the effect of options trading on innovation should be more pronounced for younger CEOs. If anything, it should increase the impact because career concerns are stronger when managers are further from retirement, as that increases the returns from influencing the market's belief about their abilities. For this reason, the investment decisions of younger CEOs should be more affected by their career concerns than those of older CEOs.

Table 2.9 presents evidence on the interaction between CEOs' age and options trading on innovation. The estimate in column 2 of Table 2.9 confirms our conjecture and shows a negative coefficient on the interaction term (-0.368) that is statistically significant at the 5% level. Consistent with our earlier findings, the coefficient on *Ln(Optvol)* continues to be positive and significant at the 1% level, while the coefficient on *CEO age* is negative (older CEOs are less innovative), although the effect is not significant.

Table 2.9
Options volume and innovation–CEO age

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)		-0.368**		-0.163
x Ln(CEO age)		(0.162)		(0.147)
Ln(Optvol)	0.166***	0.162***	0.161***	0.159***
	(0.044)	(0.043)	(0.035)	(0.035)
Ln(CEO age)	-0.245	-0.113	-0.309	-0.250
	(0.389)	(0.375)	(0.339)	(0.323)
InstOwn	0.005	0.036	-0.026	-0.012
	(0.227)	(0.226)	(0.202)	(0.203)
Ln(K/L)	0.050	0.045	0.097	0.095
	(0.083)	(0.082)	(0.068)	(0.068)
Ln(Sales)	0.299***	0.301***	0.241***	0.241***
	(0.068)	(0.069)	(0.060)	(0.060)
Ln(Age)	-0.155	-0.149	-0.086	-0.084
	(0.132)	(0.132)	(0.113)	(0.113)
Ln(R&D stock)	0.151***	0.155***	0.126**	0.128**
	(0.051)	(0.052)	(0.051)	(0.052)
Observations	1,996	1,996	1,996	1,996

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), *CEO age*, their interaction, and other firm-level control variables. Firms in columns: 337. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). CEO age is based on data from ExecuComp over the period 1996 – 2004. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.4 Profitability

To strengthen our explanation, in this section, we analyze an additional economic mechanism that is supposed to directly increase the market pressure imposed by investors–a decline in profitability. Specifically, Kothari (2001) finds that financial reporting conveys substantial information to outsiders regarding firm performance that significantly influences market expectations and stock prices. Moreover, survey evidence reveals that profitability is the most important externally reported performance measure and that the majority of managers are willing to cut discretionary spending (e.g., R&D) to meet or exceed benchmarks (Graham, Harvey, and Rajgopal, 2005). Thus, the short-term pressure imposed by external agents might be substantially more pronounced for firms with earnings that reflect decreasing profitability because investors are more likely to exit based on this negative information and the stock price may decline. Managers in these firms are also at greater risk of being fired because boards aggressively fire CEOs for lower performance (Jenter and Lewellen, 2014). In sum, if it is true that options trading activity shields managers from short-term market pressures (and the risk of being fired), we expect the positive effect of options trading to be magnified for firms with a decline in profitability.

Table 2.10 reports the results. In column 1, we regress the citation-weighted patent count on the lagged change in profitability (adjusted by assets) and options trading (and all other controls). We find that higher profitability growth has a negative association with innovation, but the effect is not significant, while the coefficient estimate on *Ln(Optvol)* remains positive and significant. Column 2 interacts the profitability variable with options volume. The coefficient on this interaction is negative and significant at the 1% level, suggesting that innovation is more sensitive to options trading when firms' profitability growth is lower. As before, columns 3 and 4 of Table 2.10 present the robustness test by replacing the dependent variable with simple patent counts. Although we observe a similar pattern, the coefficient on the interaction term is insignificant. This is interesting, however, because at face value, this result combined with the insignificant interactions in Tables 2.8 and 2.9 when the dependent variable is replaced with *Ln(1+PATS)* indicate that the effect of our mechanism stems from its impact on R&D quality rather than on higher patent propensities.

Table 2.10
Options volume and innovation–Profitability

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)		-0.308***		-0.127
x Δ ROA$_{t-1}$		(0.116)		(0.082)
Ln(Optvol)	0.176***	0.173***	0.165***	0.163***
	(0.033)	(0.033)	(0.028)	(0.028)
Δ ROA$_{t-1}$	-0.256	0.517	-0.062	0.258
	(0.229)	(0.386)	(0.151)	(0.265)
InstOwn	-0.124	-0.124	-0.245	-0.245
	(0.175)	(0.175)	(0.158)	(0.158)
Ln(K/L)	0.052	0.053	0.066	0.066
	(0.058)	(0.058)	(0.051)	(0.051)
Ln(Sales)	0.121***	0.119**	0.128***	0.127***
	(0.047)	(0.047)	(0.039)	(0.039)
Ln(Age)	-0.088	-0.088	-0.032	-0.032
	(0.094)	(0.095)	(0.081)	(0.081)
Ln(R&D stock)	0.259***	0.260***	0.205***	0.206***
	(0.052)	(0.052)	(0.049)	(0.049)
Observations	2,658	2,658	2,658	2,658

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), lagged change in profitability (Δ ROA_{t-1}), their interaction, and other firm-level control variables. Firms in columns: 526. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5.5 CEO compensation

Thus far, we have not considered how managerial compensation can help to motivate innovation. Under the optimal contracting view (Holmström and Tirole, 1993), it is efficient for firms in active option markets to grant their managers more stock- and less cash-based pay, as prices are more informative. Moreover, managerial compensation packages that are closely tied to stock prices may decrease risk aversion and motivate the manager to expend effort in long-term intangible assets. In particular, it is commonly argued that incentives in the form of stock options prevent managers from making myopic decisions and provide them with increased incentives to take on risky projects. Consistent with this, Coles, Daniel, and Naveen (2006) find that compensation structures with higher vega incentives (controlling for delta) are associated with riskier investment policy as captured by increased R&D, increased focus, and reduced PP&E. Similarly, Francis, Hasan, and Sharma (2011) show that incentives in the form of vested and unvested options have a positive and significant effect on patents and citations. Hence, it is possible that part of the positive effect of options trading activity on innovation might be attributable to contractual incentives. We explore this explicitly by conditioning on executive compensation schemes.

The data on compensation come from ExecuComp. Following prior literature (e.g., Coles, Daniel, and Naveen, 2006), the primary characteristics of compensation that we consider are CEO delta and CEO option holdings vega. Delta is defined as the dollar change in a CEO's stock and option portfolio for a 1% change in stock price and measures the CEO's incentives to increase the stock price. Vega is the dollar change in a CEO's option holdings for a 1% change in stock return volatility; it measures the risk-taking incentives generated by the CEO's option holdings. These values are calculated using the one-year approximation method of Core and Guay (2002). We also control for CEO cash compensation (salary plus bonus) and CEO tenure, as the number of years in office may be associated with different compensation schemes.

In column 1 of Table 2.11, we re-estimate Eq. (2.1) on the subsample of firms with non-missing compensation variables. The coefficient on *Ln(Optvol)* is 0.157 and significant at the 1% level. In column 2, we add the compensation variables. The coefficients on *Ln(*1+*CEO vega)* and *Ln(*1+*CEO delta)* are positive but insignificant, while the key coefficient on options volume continues to be positive but becomes smaller in magnitude (i.e., declines to 0.142), which represents a decrease of approximately 10% from the estimate in column 1.[32] In columns 3 and 4, we repeat the specifications of the first two columns but use patent counts as the dependent variable. We observe a similar pattern for the coefficient on *Ln(Optvol)*, i.e., it continues to be positive and significant but declines by approximately 13% once the compensation variables are included. Interestingly, the coefficient on *Ln(*1+*CEO vega)* becomes significant, which means that higher vega implies more innovative outputs (as one might expect). Overall, these findings suggest that managerial compensation schemes capture part of the size effect of options trading

[32] The insignificant coefficient on CEO delta is consistent with the result in Fang, Tian, and Tice (2014), indicating that greater pay-performance sensitivity is not associated with more innovation. This finding remains unaltered if we replace CEO delta with the scaled wealth-performance sensitivity measure of Edmans, Gabaix, and Landier (2009). In an identical specification to column 2, the coefficient (standard error) on this variable is 0.037 (0.048) whereas the coefficient (standard error) on options volume is 0.137 (0.045).

on innovation and are thus part of the story, although the specific channel underlying this mechanism is rather ambiguous.

However, taking Table 2.11 as a whole, we note that options volume has a robust positive effect on innovation across all specifications, indicating that the relationship between options trading activity and innovation goes substantially beyond compensation structures. This is what one would expect under the career concerns explanation. Specifically, although the design of the compensation contract can overcome some of the disincentives to innovate, it does not shield managers from the reputational effects of failed innovation. As Gillan, Hartzell, and Parrino (2009) show, in 2000, 54% of the firms in the S&P 500 had no explicit employment agreement with their CEOs (i.e., the CEOs were employed "at will"). The median time horizon of the remaining 45% was three years. Hence, because CEOs enter the labor market repeatedly, their payoffs are ultimately not determined by explicit contracts but by the effect their respective reputation has on their ability to contract in the future.[33]

[33] Incorporating the choice of compensation contracts as a consequence of options trading into our analysis clearly goes beyond the scope of this paper, but endogenizing this decision represents an interesting avenue for future research.

Table 2.11
Options volume and innovation–CEO compensation

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)	0.157***	0.142***	0.157***	0.137***
	(0.043)	(0.045)	(0.035)	(0.037)
Ln(1+CEO vega)		0.070		0.106***
		(0.044)		(0.033)
Ln(1+CEO delta)		0.021		0.015
		(0.058)		(0.048)
Ln(1+CEO tenure)		-0.037		-0.032
		(0.050)		(0.042)
Ln(1+CEO cash compensation)		-0.066		-0.094**
		(0.047)		(0.040)
InstOwn	-0.107	-0.125	-0.135	-0.168
	(0.204)	(0.210)	(0.188)	(0.193)
Ln(K/L)	0.013	0.022	0.048	0.058
	(0.085)	(0.086)	(0.070)	(0.069)
Ln(Sales)	0.301***	0.292***	0.254***	0.247***
	(0.072)	(0.073)	(0.063)	(0.062)
Ln(Age)	-0.164	-0.168	-0.075	-0.084
	(0.127)	(0.128)	(0.116)	(0.117)
Ln(R&D stock)	0.148***	0.145***	0.113**	0.106**
	(0.055)	(0.055)	(0.052)	(0.051)
Observations	1,845	1,845	1,845	1,845

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume *(Optvol)*, CEO compensation variables, and other firm-level control variables. Compensation variables are based on data from ExecuComp over the period 1996 – 2004. *CEO vega* is the dollar change in the CEO's wealth for a 0.01 change in the standard deviation of returns; *CEO delta* is the dollar change in the CEO's wealth for a 0.01 change in the stock price; and vega and delta values are calculated using the one-year approximation method of Core and Guay (2002). *CEO cash compensation* is the sum of CEO salary and bonus, and *CEO tenure* is the number of years the CEO has held the position. Firms in columns: 323. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.6 Discussion and conclusion

How do financial derivatives affect managerial investment decisions in the real economy? Specifically, do they hinder or promote innovation? This paper attempts to answer these questions by studying the relationship between innovation and options markets.

Our findings contrast with the view that developed financial markets exacerbate myopic behavior by managers and suggest instead that the presence of informed traders in the options market boosts innovation, even after accounting for R&D investments and the potential endogeneity of options volume. In particular, firms with more options trading activity obtain more patents and patent citations per dollar of R&D invested. We interpret these findings as evidence that the enhanced information efficiency induced by options reduces information asymmetries related to R&D, which provides managers with incentives to invest in innovation. This positive impact could derive from a change in the direction of innovative activities or an increase in R&D spending and productivity. Our findings support the former: firms with greater options trading activity pursue a more creative, diverse, and risky innovation strategy.

Our results complement those of Roll, Schwartz, and Subrahmanyam (2009), who find that option markets increase firm valuations by allowing agents to cover more contingencies and by stimulating trading on private information. Specifically, we strengthen their claims by establishing a direct link between options trading activity and managerial investment decisions and show that higher levels of options volume are associated with a more efficient allocation of R&D resources, which then translates into higher firm value. To show this, we rely on two findings. First, Hall, Jaffe, and Trajtenberg (2005) provide evidence that an extra citation per patent boosts a firm's market value by 3%. Second, we repeat the tests in Hall, Jaffe, and Trajtenberg (2005) with a slightly augmented set of control variables. We find that the raw number of patent counts and cite-weighted patent counts have a positive and significant association with a firm's market value.[34] In summary, these pieces of evidence suggest that informed traders in the options market reward successful innovation outcomes with a higher valuation. Together with the core finding of our paper that the main effect of options trading is to alter the quality of innovation outputs, the above evidence seems to reveal one possible "bright" side of financial derivatives: their positive impact on firms' market value by motivating firms to invest in innovative activities.

We discuss several possible mechanisms that could contribute to these findings. First, in line with Aghion, Van Reenen, and Zingales (2013) and contrary to the view that informed traders have a disciplinary effect on managers by "forcing" them to innovate, we find that the presence of informed traders improves the incentives to innovate by reducing career concerns. The beneficial effect of options trading is more pronounced when product market competition is intense, when managers are less entrenched, and for younger CEOs. We complement their findings by showing that informed agents play a crucial role in motivating innovation, even if these agents cannot intervene directly in firms' operations (i.e., compared to blockholders). Second, given the pressure from investors to meet profitability targets, decreasing investments in innovation is one of the major real earnings management tools that managers often use to report positive or increasing income. Our analysis indicates that informed traders do recognize the consequences of cutting R&D activities and therefore mitigate myopic investment problems. Finally, we show that the role of informed trading in motivating innovation exists beyond the structure of managerial compensation and corresponding incentives. Although compensation is a mechanism that links options trading activity and innovation, this effect appears to be substantially dominated by reputation-based incentives, at least in our setting.

While our findings on these mechanisms are consistent with our theory, an unanswered question remains, namely, what is the bottom-line impact of options trading on innovation after accounting for the proposed economic mechanisms. To that end, we directly control for all five mechanism variables and re-estimate an augmented version of Eq. (2.1). The results are

[34] These results are tabulated in Table A.14 in the Appendix.

tabulated in the Appendix, Table A.15. Overall, we find that options trading continues to be positively and significantly (at the 1% level) related to innovation even after controlling for its dependence on these mechanisms but becomes smaller in magnitude (i.e., declines from 0.216 to 0.154), which reflects a 29% decrease from the baseline model.[35] This suggests that while our mechanisms are able to explain a significant proportion of the positive effect of options trading on innovation, the remaining effect remains strikingly large. Specifically, a coefficient of 0.154 suggests that an increase of 200% in the dollar volume of options traded is associated with a 31% increase in cite-weighted patents. For the median firm in this subsample, this implies that an increase in the trading volume from \$15 million to \$45 million leads to approximately seven additional cite-weighted patents (i.e., from 21 to 28). This result is both economically and statistically significant.

Clearly, we made some simplifying assumptions throughout the paper. Specifically, we assume that managers can influence corporate innovation. However, even in the absence of a specific link, there are several reasons to believe that managers can indeed influence patent-based measures of innovation. As Lerner and Wulf (2007) emphasize, managers can change the compensation schemes of R&D executives toward more long-term incentives, which can significantly improve the quality of innovative outputs. Managers could also initiate reorganizations with new strategic priorities. For instance, Daniel Vasella, the CEO of Novartis from 1996 to 2010, generated a large increase in R&D productivity with two major strategic moves. First, Vasella expanded Novartis's research from a narrow focus on internal discovery and development capabilities to exploration in new areas through extensive collaborations and the establishment of science-based research institutes. Second, he assigned budget and performance responsibilities over R&D to the business units by setting precise goals, cutting waste, and rewarding successful innovators (Datar and Reavis, 2003).

Moreover, while our study draws on one particular "bright" side of financial derivatives, we are agnostic about how these instruments may affect other stakeholder groups in other ways. Although innovation is important for the growth and wealth of nations, we do not conclude that the greater research productivity shown in our study enhances social welfare. With estimates of the current size of the market for derivatives at approximately \$700 trillion, this should, however, be a concern for academics, government regulators, managers, and investors. We leave a proper evaluation of the net effects of financial derivatives for future research.

[35] To avoid excessive missing values in this test, we fill in years missing the G-Index with the preceding year's G-Index. Further, note that the magnitude of the baseline estimate differs from that reported in Table 2.2, column 4, because we have only a subsample of firms (i.e., firms included in the S&P 1500 index) with non-missing mechanism variables. This allows us to compare the change in coefficients on the same observations.

Chapter 3

The Effect of Patent Protection on Inventor Mobility

3.1 Introduction

The patent system is a major instrument for articulating government innovation policy. Patent rights are expected to provide incentives for innovation and to foster the diffusion of knowledge. Economists, legal scholars and policy advisors, however, have long questioned the effectiveness and efficiency of the patent system in reaching these goals (see, e.g., Federal Trade Commission, 2003). First, awarding monopoly rights as a reward for innovation involves the obvious deadweight loss and rent-seeking costs associated with monopolies (Nordhaus, 1969; Boldrin and Levine, 2013). Furthermore, it is unclear whether patents help or hinder the diffusion of knowledge and, ultimately, the generation of further innovation. On the one hand, historical evidence shows that the use of patent protection encouraged the geographical diffusion of innovations in the chemical industry (Moser, 2011) and the exchange of ideas in markets for technology (Lamoreaux and Sokoloff, 1999). On the other hand, increased fragmentation of ownership rights among firms, combined with the recombinant nature of new knowledge, may lead to steep increases in the transaction costs associated with transferring patent-protected knowledge (Heller and Eisenberg, 1998), thus hampering its diffusion. Recent research on the impact of patents on subsequent innovation is also inconclusive. While Galasso and Schankerman (2015) provide evidence of substantial increases in citations of patents that are invalidated by courts, Sampat and Williams (2015) show that patents on genes do not hinder subsequent related innovations.

Complementing this debate on patents and the diffusion of knowledge, this article studies an indirect, albeit important, mechanism through which patents may affect the circulation of knowledge: inventor mobility. Since Arrow (1962, p. 615) noted that "mobility of personnel among firms provides a way of spreading information," economists have identified labor mobility as a key conduit through which knowledge spillovers occur. In this respect, the mobility of the R&D personnel responsible for technological advances is particularly relevant. Previous research has documented the inter-firm transfer of technical knowledge following inventor moves (Almeida and Kogut, 1999; Maliranta, Mohnen, and Rouvinen, 2009; Singh and Agrawal, 2011). Therefore, understanding the causal relationship between patent protection and inventor mobility will allow us to have a more complete picture of the role of patents in the diffusion of knowledge.

We explicitly explore the effect of patenting on the career moves of the inventors responsible for the underlying innovations. Following the existing literature on intellectual property (IP) rights, we hypothesize a negative effect of patents on inventor mobility. Patents grant their owners (usually the employer of the inventor) a time-limited right to prevent others from using a given technology. Consequently, they restrict the amount of knowledge that an inventor can effectively use following a move to a new employer (Kim and Marschke, 2005; Agarwal, Ganco, and Ziedonis, 2009). Furthermore, by conferring monopoly power over a given technology, patent rights increase the value of retaining the creators of that technology in the implementation phase. This makes the human capital of inventors with (issued) patents more specific to their current employers and makes them less likely to move.

Testing the aforementioned hypothesis poses an important methodological challenge. Since patented innovations are inherently different from non-patented ones (as their inventors are also likely to be), a simple comparison of inventors who patent with those who do not might lead to conclusions that only mirror the underlying dissimilarities. First, the firm decision to apply for patent protection depends on the characteristics of the given innovation (see Criscuolo, Alexy, Sharapov, and Salter, 2015), which may also reflect certain attributes of the human capital of its inventor(s). Second, the decision to apply for a patent is likely to be affected by the dynamism of the inventor labor market, as suggested by Kim and Marschke (2005). Moreover, the applications that are finally granted patents are a selected group of innovations, namely, those that imply sufficient advancement in the state of the art according to the patent office requirements (i.e., novelty and non-obviousness of the inventive step). These requirements are arguably more likely to be achieved by talented inventors. Hence, a straightforward comparison between patented and non-patented innovations is not appropriate.

We investigate the effect of patenting on inventor mobility by comparing the trajectories of inventors with different numbers of applications granted a patent. In order to estimate the causal relationship, we use variation in leniency across patent examiners as a source of exogenous variation in granted patents. Patent examiner leniency has been recently used as an instrumental variable to estimate the effect of patents on subsequent cumulative innovation (Sampat and Williams, 2015) and on venture capital-backed startup success (Gaulé, 2015; Farre-Mensa, Hegde, and Ljungqvist, 2017). The validity of this instrument is supported by interviews with employees of the United States Patent and Trademark Office (USPTO) regarding the allocation of patent applications to examiners (Cockburn, Kortum, and Stern, 2003; Lemley and Sampat, 2012), as well as by our own exogeneity tests.

Our empirical analysis is based on the career trajectories of 69,136 inventors who filed their first patent application with the USPTO between 2001 and 2012. By identifying individual inventors' career moves from patent application data, our results point to a negative effect of patenting on mobility. In particular, one additional patent granted (due to a "lucky" examiner assignment) decreases an inventor's probability of changing employers by 25 percent. This negative effect increases to 42 percent for "discrete" technologies (such as pharmaceuticals and chemicals), where individual inventions are more clearly linked to marketable products and patent rights protect them more effectively (Cohen, Nelson, and Walsh, 2000). On the other hand, the estimated effect is much weaker in "complex" technologies (such as electronics), where a given product is typically associated with many potentially patentable elements, meaning that an individual patent confers less protection on the final product. Overall, these results suggest that, by providing firms with monopoly power over a given technology, patents make the human capital of the creators of the underlying innovation more specific to the current employer. Additional tests show that the negative effect of patenting on mobility is stronger for inventors with fewer co-authors and for inventors working outside the technological core of their firm, suggesting that patents play a stronger role in the absence of other sources of firm-specific human capital. Finally, and consistent with our specific human capital hypothesis, we document that patents most steeply decrease the mobility of inventors to firms that work in the same core technological areas as their current employers.

The results of our study provide new insights into several domains. First, we contribute to research on knowledge diffusion and inventor mobility by showing that the institutional effect of the patent offices on mobility is not neutral. Scholars have traditionally relied on patent data to examine the impact on mobility of institutional factors such as trade-secret laws or non-compete contracts (Fallick, Fleischman, and Rebitzer, 2006; Marx, Strumsky, and Fleming, 2009; Png and Samila, 2015) and inventors characteristics such as productivity (Hoisl, 2006; Palomeras and Melero, 2010). However, little is known about whether and how the mobility of those employees is itself affected by patents. Our study aligns with recent work by Agarwal, Ganco, and Ziedonis (2009) and Ganco, Ziedonis, and Agarwal (2015), who show that the degree of litigiousness of patent-holding firms is related to the amount of knowledge that moving inventors can effectively transfer and, consequently, to inventor turnover rates. In this respect, our paper provides evidence on the causal role that patent grants play in the overall process. Second, our paper adds a dimension to the ongoing debate over the role of patents in innovation policy. The design of a patent system is expected to address the tradeoff between the incentive to innovate and the diffusion of knowledge. Our results suggest that, by reducing the inter-firm mobility of inventors, patents may preclude the transmission not only of formally protected knowledge but also of tacit technical and organizational knowledge. The findings also imply that patents may shift incentives to invest in inventive skills from the employee-inventors to the patent-holding employers. Finally, our results have an important methodological implication. Many research questions in the area of innovation have traditionally been addressed using data on granted patents, from mobility studies to knowledge spillover estimations and co-inventor network analyses. Our evidence indicates that future research should take into account the effect of patent grants on the behavior of inventors and subsequent knowledge flows in order to avoid potentially biased results.

3.2 Background

The thesis of this article is that granted patents make the human capital of the inventors more specific to their employers. It builds upon the idea that patent rights provide their owners with an increased ability to protect their intellectual assets and, consequently, to obtain a monopoly over the underlying technology.[1] In addition, the labor contracts of R&D workers typically include provisions by which employers retain property rights over their employees' inventions. This implies that patents effectively constrain the inventor from freely using that protected knowledge. The consequences for mobility, however, are not straightforward.

The first element to take into account is the balance of incentives of current employers and rivals to bid for the inventor. Consider first the author of an innovation that, because of a lack of patent rights, is only weakly protected. On the one hand, the ability of competitors to replicate the invention would be clearly enhanced by employing the original inventor. Thus, they have incentives to poach her. On the other hand, the current employer may also have strong incentives to retain the inventor in order to secure monopoly profits by preventing her from moving to a competitor. The joint-profit effect (Budd, Harris, and Vickers, 1993) suggests that,

[1] Survey evidence gathered by Cohen, Nelson, and Walsh (2000) suggests that firms may prefer alternative mechanisms of protection, such as secrecy or lead times, over patents in a wide range of settings. Our study considers the universe of inventions for which an application for patent protection has been filed. Therefore, it seems reasonable to assume that applicants in this population expect to obtain an increase in protection from a granted patent.

in the absence of strong property rights, incumbents will have stronger incentives than their rivals to bid for their inventors, unless their products are differentiated enough in the market (Fosfuri, Motta, and Rønde, 2001).[2] Suppose that the incumbent now increases the protection of an innovation by obtaining a patent. To the extent that property rights prevent the unauthorized commercial exploitation of technological replicas by rivals, patents will eliminate the above-mentioned strategic incentives to either poach inventors (rivals) or retain them (incumbents) because rivals cannot use the inventors' knowledge for replication and incumbents do not need to retain the inventor to secure monopoly profits. Thus, the *appropriation effect* of patent grants on inventor mobility may be positive or negative, depending on the degree of differentiation among the products of the incumbent and its rivals. In a non-differentiated market, the incumbent's incentives to retain the inventor disappear with (strong) patents, so mobility increases with respect to a situation without property rights. In a differentiated market, rivals' incentives to poach the inventor tend to disappear with patents, and thus, mobility decreases with respect to a situation without patents.

A second important element to consider is the relevance of the inventors' knowledge for the successful implementation of an innovation by a patent holder. While patents may allow their holders to obtain monopoly profits when bringing the innovation to the market, the involvement of the inventor in implementation activities can enhance the exploitation of this monopoly power. This makes the human capital of inventors effectively complementary to patent protection. The development of an innovation into an actual product (or process) ready to be launched in the market (or internally implemented) is not a trivial task, and it usually benefits considerably from the involvement of the creator(s) of the innovation. In a study of licensing contracts for patented inventions in the biomedical industry, Hegde (2014) reports the use of clauses specifying the complementary knowledge that should be transferred to the licensee along with the patent in order to successfully develop the innovation. Some of these clauses explicitly require the personal involvement of the inventor in the process, as well as monetary compensation for their effort. These cases illustrate the importance of non-codified knowledge for the implementation of patented technologies, particularly the involvement of their creators. Maurseth and Svensson (2015) provide further evidence suggesting the importance of the inventor's involvement in successfully bringing an innovation to market using a sample of commercially exploited patents generated by small firms. This evidence indicates that inventors are inputs in the implementation of their innovation and that they are especially valuable when the latter is patent protected. According to this *complementarity effect*, therefore, patents increase the internal value of the inventor to the patent holder, generating some firm-specific human capital and decreasing the probability that inventors switch employers.

In sum, we expect patents to reduce inventor mobility to the extent that they confer monopoly power that can only be fully exploited by keeping the inventor in-house (complementarity effect) and that alternative employers develop sufficiently differentiated products (ap-

[2] In a non-differentiated market, an incumbent's incentives to maintain a monopoly situation (as opposed to a duopoly one) will be greater than or equal to those of rivals seeking duopoly profits. As noted by Fosfuri, Motta, and Rønde (2001), however, this is not necessarily the case if there is some product differentiation or if the intensity of competition is low.

propriation effect). In empirical terms, previous related research reports that the relationship between property rights protection and mobility goes in this direction. Kim and Marschke (2005) provide evidence that innovative firms tend to file for patent protection more in contexts with highly dynamic R&D labor markets. However, they do not specifically study the direction of the effect of patents on mobility. In a related study, Ganco, Ziedonis, and Agarwal (2015) find that the outbound mobility of the inventors of patented innovations is significantly lower in innovative firms with strong reputations for patent litigation. Outside the realm of patent enforcement, Png and Samila (2015) show that the mobility of qualified workers is lower in U.S. states with stronger enforcement of trade-secret laws.

If patents have a detrimental effect on inventor mobility because their human capital becomes relatively more valuable to their current employer, we should expect that the impact on mobility is heterogeneous across contingencies. First, our argument that the negative effect of patents on mobility is caused by the monopoly power they confer implies that the size of the impact should differ with the effectiveness of patent protection across technology fields. Both the appropriation effect (resulting from changes in the balance of incentives to poach and retain the inventor) and the complementarity effect (arising from the role of the inventor in the implementation of the innovation) will be more intense when patents offer stronger protection. Therefore, the negative effect of patents on mobility will be more pronounced in settings of higher patent effectiveness.

Second, we expect other sources of inventors' firm-specific human capital to act as substitutes for patent protection. Workers' firm-specific skills are tied to a particular firm and have limited applicability to outside firms. This results in a lower relative outside value of employees' human capital in the labor market and leads to a lower probability of turnover (Becker, 1962). In particular, patents operate as a source of specificity of an inventor's human capital by creating a legally induced gap between the inside and the outside value of her skills that reduces her probability of moving. We expect this effect to be weaker when other sources of complementarity (either legally or technically induced) with the current employer make an inventor's skills firm specific. The reason is that if an inventor's skills are already firm specific, she will be unable to fully apply her skills at a new employer, even if the underlying knowledge is not patented. In contrast, when the inventor's skills are general and can be readily applied to alternative employers, patent protection should have a larger negative effect on mobility.

Third, obtaining a patent may affect different types of inter-firm moves differently. Inventors may be induced to leave their companies for a variety of reasons, and replicating their innovations elsewhere may be only one of them. The above discussion of how patents affect the balance of bids to appropriate the knowledge associated with the innovation only concerns firms that are close enough in the technological space to be able to implement this technology. Firms that are technologically distant can also be considered alternative employers of the focal firm's inventors, but they are less likely to be interested in the specific innovation than are technologically close competitors. Hence, the appropriation effect of patents on mobility will be weaker for moves to technologically distant employers. On the other hand, the complementarity effect will reduce the probability of moving to any alternative employer, since it only concerns the internal value of the employment relationship between the inventor and the patent-holder. Thus, we expect that even if patents reduce inventor mobility to both technologically distant and technologically close firms, the effect will be more pronounced for moves to the latter group of employers as long as they market sufficiently differentiated products.

3.3 Description of the data

Our paper combines data from several sources. Our starting point is the USPTO Patent Examination Research (PatEx) dataset, which sources its information from the public Patent Application Information Retrieval (PAIR) database. PAIR contains detailed information on patent applications filed with the USPTO. For each application, it includes characteristics such as the filing date, application type, patent class and subclass codes and current application status, as well as data about the examination, such as the identity of the assigned examiner and the "art unit" to which he belongs. From this dataset, we identify every original utility patent application filed between 2001 and 2012, which totaled 3.6 million applications. We are constrained to this time period due to data availability. The PAIR dataset contains data only on applications that have been published (i.e., that are open to public scrutiny), and it was not until late 2000 that applications were made public before a patent was granted following the implementation of the American Inventors Protection Act (AIPA). This means that since November 2000, publication happens regardless of whether the patent is granted, whereas previously, only applications that were eventually issued patents were published. As Graham, Marco, and Miller (2015) report, PAIR has very good coverage (95%) of regular utility filings from 2001 to 2012 (after that, truncation due to a publication lag affects coverage).[3]

We next turn to the information available from the USPTO Patent Assignment Dataset, since the PAIR database does not identify the assignee (i.e., the firm) responsible for filing the patent. Before September 2012, the USPTO considered the inventor to be the owner of a patent application. However, inventors typically have contractual obligations to transfer ownership to their employer. In order to do so, it was necessary to submit a chain of title from the original owner (i.e., the inventor) to the assignee (i.e., the firm) to the patent office so that the legal assignment could be made.[4] The dataset tags those assignments, allowing us to identify the assignee and the presumed employer of an inventor. From our original set of patent applications, we identify 2.8 million applications that were re-assigned from the inventors to the employers.

Thereafter, we use data from the PatentsView initiative (www.patentsview.org) to identify the inventors listed in our sample of applications and compile their career histories. This dataset contains the results of the disambiguation algorithm specific for inventor data provided in Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014) and Balsmeier, Chavosh, Li, Fierro, Johnson, Kaulagi, O'Reagan, Yeh, and Fleming (2015), which allows the robust identification of individual inventors across patent applications (since 2001) and granted patents (since 1976).[5]

[3]The remaining 5% of applications corresponds to those that were abandoned before the 18-month publication lag, those that opted out of pre-grant publication (relinquishing the possibility of international protection) at that moment and those applications for which patents were not granted (Graham, Marco, and Miller, 2015). According to these authors, who had access to internal USPTO application records, the applications covered by PatEx are very similar to the population of USPTO applications.

[4]See 37 CFR 3.71 (pre-AIA), 35 U.S.C. 261 and Marco, Myers, Graham, D'Agostino, and Apple (2015) for details.

[5]We are grateful to the PatentsView team for sharing this data with us. PatentsView is supported by the

Through these data, we can identify 2.1 million disambiguated individual inventors.

This initial set of inventors is substantially reduced due to the restrictions we impose. First, we focus our analysis on inventors who filed their first patent application between 2001 and 2012. This sample represents a selection of inventors who are in their early careers, that is, in the ten first years (at most) of inventive activity. We select these inventors for two main reasons. Primarily, the initial steps of an inventor's career are more likely to be affected by the outcome of one or a few patent applications. Thus, if an effect of patents on mobility exists, it will be more clearly detected among inventors beginning their careers. Moreover, regression to the mean in random processes eliminates variation in average patent examiner leniency among inventors with a large number of applications. Thus, our identification strategy would be less effective for the subpopulation of very experienced inventors. Accordingly, we select only inventors with no prior patenting experience before our sample period (i.e., before 2001).

Second, given our aim to detect the impact of the decision of the patent office, we focus on inventors who receive at least one decision on an application during our sample period. In particular, we require that they receive a first decision on their application prior to 2012 in order to ensure that we have at least a nine-month window in which to observe mobility for the last cohort in the data.[6]

Given our interest in employee inventors, we further restrict our sample to inventors who started their careers (as measured by their patent filings) at a company. In order to capture them, we select applications assigned to originating firms included in the Standard and Poor's (S&P) Capital IQ database, which provides the names and transactions (such as mergers and acquisitions) for the most extensive set of public and privately held U.S. firms (to the best of our knowledge). In order to match the firm names from Capital IQ with the assignee names, we first apply the name standardization procedure used in the NBER patent data project.[7] We then run the Jaro-Winkler algorithm (developed to assist in the disambiguation of names in the U.S. Census) to correct for typos and misspellings, grouping together records with an overlap of 90% or higher. Finally, we keep the final list of standardized assignee names that coincide exactly with firm names in Capital IQ.

Following the previous literature, we infer inventor mobility based on a change in the assignee between two consecutive applications (see, e.g., Almeida and Kogut, 1999; Trajtenberg, Shiff, and Melamed, 2006; Marx, Strumsky, and Fleming, 2009; Singh and Agrawal, 2011; Ganco, Ziedonis, and Agarwal, 2015). This approach has a number of acknowledged limitations (Palomeras and Melero, 2010; Ge, Huang, and Png, 2016). First, an inventor's career can only be tracked if she is included repeatedly in patent applications. Otherwise, she is censored out of the sample. One potential concern is that inventors whose applications have not been granted may be less likely to apply again in the future.[8] To the extent that this attrition effect concerns similarly

Office of the Chief Economist at the USPTO, with additional support from the U.S. Department of Agriculture (USDA). The PatentsView platform was established in 2012 and is a collaboration among the USPTO, USDA, Center for the Science of Science and Innovation Policy at the American Institutes for Research, University of California, Berkeley, Twin Arch Technologies, and Periscopic.

[6]Note that our observation period effectively runs until September 2012 when the previously mentioned legal assignment regime changed from inventors to their firms.

[7]See https://sites.google.com/site/patentdataproject.

[8]For example, while 50.6% of individuals whose first patent application was not granted never filed an applica-

moving inventors and stayers, it would not affect our estimation of the relationship between patent grants and mobility. A more serious concern is that differences among firm patenting policies lead inventors that switch employers to differ from stayers in their probability of being included in a future application. After all, applying for patents is to a large extent a firm-level decision, and there may be substantial heterogeneity among firms in the intensity of patent use. All the inventors in our population have, by definition, been included in a patent application by their initial employers. Thus, it is natural to expect that all inventors are initially employed by a firm with relatively high levels of patent intensity and that moving inventors will switch, on average, to less patent-intensive employers. This would imply that that our overall mobility rates would be underestimated and, more importantly, that our estimated effect of patent grants on mobility would be subject to attenuation bias. We address this issue in Section 3.5.3.

Second, identifying inventors through the names that appear in patent documents is subject to errors. We mitigate them by using the disambiguation algorithm provided by Balsmeier, Chavosh, Li, Fierro, Johnson, Kaulagi, O'Reagan, Yeh, and Fleming (2015). Other important sources of misclassification in tracking mobility with patent data are the inability to detect the exact point in time at which a moves take place (not problematic for our study) and the recording as moves of contract R&D, collaborations, mergers or acquisitions.[9] We address this last problem by imposing some restrictions in order to consider a change in assignee as an actual move: (i) we do not consider changes in the assignee that imply returns to an original employer in less than one year from the supposed move (as in Ge, Huang, and Png, 2016) under the assumption that they probably reflect contract research or collaborations; and (ii) we do not consider apparent changes in employers due to mergers and acquisitions, which are detected through information provided by Capital IQ. The existence of some remaining misclassification error is unavoidable due to the nature of the large-scale representative sample used in our study.

Thus, our final sample consists of inventors who started their research lives at one of our identified Capital IQ firms during the period 2001-2011 and who receive a first decision on a patent application prior to 2012. We track inventors from their first application until they move or until their last application (during the sample period) with the originating firm. The resulting dataset comprises 69,136 first-time inventors employed by 2,883 originating firms that filed 404,016 patent applications during the sample period. In total, we detect 13,984 first-employer changes for those inventors, averaging 0.20 moves per inventor.

tion again, the corresponding percentage decreases to 44.4% for individuals whose first application was granted.

[9] These errors are highlighted in Ge, Huang, and Png (2016), which attempts to detect the misclassification problems produced by the use of patent data to track mobility. The authors compare the mobility detected with patent data with that inferred from a small (and unavoidably biased) sample of LinkedIn public and self-reported profiles for patenting inventors. Because of a lack of representativeness of their sample, their results must be interpreted with caution.

3.4 Econometric modeling strategy

3.4.1 Baseline specification

To identify how the approval of an inventor's patent application affects subsequent mobility, we estimate the likelihood that an individual changes her employer between application year t and application year $t+1$, conditional on not having moved at t. We use a linear probability model to estimate the hazard that an inventor moves:

$$Probability_{it}\ (Y_{i,t+1} = 1) = \alpha + \beta\ Patents\ granted_{it} + \gamma\ Z_{it} + \delta\ S_i + \varepsilon_{it}, \tag{3.1}$$

where i indexes inventors, and t indexes application years (i.e., the number of years in which the inventor has filed at least one application up to that point). The dependent variable, $Y_{i,t+1}$, is an indicator that equals one if an inventor moves between t and $t+1$. Note that we consolidate the information on applications on an annual basis, so our measure of mobility records whether the inventor changed employers at least once during that observation window. Our main variable of interest, $Patents\ granted_{it}$, is the total number of patents issued to inventor i up to (and including) spell t. The vector Z_{it} contains a range of time-variant covariates. First, and most importantly, Z_{it} contains the total number of applications filed by inventor i up to spell t. We also condition on the time elapsed since the inventor's first decision year, allowing mobility decisions to be shaped by seniority. To account for sectoral differences in mobility rates, we include indicators for six non-exclusive NBER categories in which applications are classified. Finally, S_i represents the year in which the inventor receives her first decision from the patent office. This cohort indicator controls for the fact that inventors entering later in the panel have less time to move than do those entering earlier. We cluster standard errors at the inventor level.

3.4.2 Identification strategy

As discussed in the introduction, an important concern is that β will likely be biased upwards, since it captures the combined impact of patents granted and omitted inventor characteristics. For example, inventors of higher quality are more likely to be the authors of inventions that meet USPTO criteria for approval.[10] Since those inventors are also more likely to be hired away (Palomeras and Melero, 2010), this may confound any true causal effect. To overcome this identification challenge, we use examiner leniency as an instrument for whether an inventor's applications are approved by the patent office and estimate Eq. (3.1) using a two-stage least squares (2SLS) approach (see Gaulé, 2015; Sampat and Williams, 2015; Farre-Mensa, Hegde, and Ljungqvist, 2017). This instrument was first proposed by Sampat and Williams (2015) based on the work of Lemley and Sampat (2012) and Cockburn, Kortum, and Stern (2003) on the processes and outcomes of patent examination at the USPTO. We next describe this process

[10]The USPTO assesses whether applications should be granted patents based on the following five criteria: patent eligibility (35 U.S.C. 101), novelty (35 U.S.C. 102), non-obviousness (35 U.S.C. 103), usefulness (35 U.S.C. 101), and an application that satisfies the disclosure requirements (35 U.S.C. 112).

to illustrate the rationale for the instrument.

Rationale for the instrument: The examination process

Patent examiners at the patent office are key figures in the examination process of a patent application. Their decisions determine eventual approval or rejection. Recent studies suggest that the odds of receiving a patent depend on the characteristics of the particular examiner assigned to the application (Lemley and Sampat, 2012; Frakes and Wasserman, 2016). In their sample, Lemley and Sampat (2012) find an 11-percentage-point difference in the grant rate between the least and the most experienced examiners who check applications related to a given technology. Frakes and Wasserman (2016) report differences in the odds of patent approval by examiner cohort (i.e., the year in which they were hired), which they attribute to differences in the training received that mirrored patent office policies at that time. There is also evidence that certain characteristics of granted patents differ by examiner.[11] Cockburn, Kortum, and Stern (2003) and Lichtman (2004) acknowledge that patent examination is not a mechanical process and, therefore, examiners necessarily enjoy some discretion in how they conduct the examination and determine its outcome. Nevertheless, the allocation of applications to examiners at the USPTO follows certain structured steps that guarantee virtually random assignment within a given technological area (Cockburn, Kortum, and Stern, 2003; Lemley and Sampat, 2012).

At the USPTO, patent applications are received by a central office, where they are assigned an application number, a patent class and subclass codes and allocated accordingly to one of the art units in charge of the examination process. Art units are groups of examiners that specialize in a given set of technologies (there are more art units than patent classes but fewer than subclasses). Once a patent is allocated to an art unit, a supervisory patent examiner (SPE) receives the application and assigns it to a specific examiner. Each art unit is an independent administrative division and has discretion in how work is organized, including how applications are allocated to examiners. Interviews with patent examiners conducted by Lemley and Sampat (2012) reveal that supervisory examiners make most final decisions on the assignment of applications to examiners on a quasi-random basis (e.g., according to docket management needs or following arbitrary rules, such as the last digit of the application number). There is no evidence from these interviews that SPEs engage in any substantive evaluation of applications in order to detect their patent-worthiness. Therefore, it is unlikely that they assign applications to certain examiners according to such characteristics. Both Lemley and Sampat (2012) and Sampat and Williams (2015) show that patent applications assigned to lenient and strict patent examiners have similar observable characteristics at the time of application (number of pages, family size and number of claims). In Appendix B.1, we replicate this exercise for other relevant pre-determined factors, such as the size of the applicant or the number of references to the patent and non-patent literature submitted in the application. Our results do not show a significant relationship between these factors and examiner leniency. Hence, the evidence at hand

[11] In a small and very selective sample (180 granted patents brought to the Court of Appeals at the end of the nineties), Cockburn, Kortum, and Stern (2003) note that characteristics such as prior citations introduced by the examiner, citations received afterwards and the odds of being declared invalid by the courts vary with the characteristics of the examiners.

suggests that the assignment of applications to examiners can be reasonably assumed to be essentially random within a given art unit. Consequently, we follow Sampat and Williams (2015), Gaulé (2015), and Farre-Mensa, Hegde, and Ljungqvist (2017) in using examiner leniency as an instrument for application approval.

The instrument: Average examiner leniency

Our objective is to obtain an instrumental variable for the number of applications granted to an inventor up to a given point in time. We start by operationalizing examiner leniency at the application level. In the spirit of Gaulé (2015), we compute time-varying measures of leniency as follows:

$$E_{jkat} = \frac{Grants_{kat} - 1(Grant_j = 1)}{Reviews_{kat} - 1} \tag{3.2}$$

and

$$U_{jat} = \frac{Grants_{at} - 1(Grant_j = 1)}{Reviews_{at} - 1}, \tag{3.3}$$

where E_{jkat} is the approval rate of examiner k in art unit a assigned to review patent application j submitted at time t. $Reviews_{kat}$ and $Grants_{kat}$ are the numbers of applications examiner k has reviewed and granted, respectively, in art unit a in the same application year as j.[12] Similarly, U_{jat} is the approval rate of art unit a and is constructed as the share of reviewed applications filed in the same year as application j that were granted by art unit a, excluding the focal patent.[13] The difference between E_{jkat} and U_{jat} is hence the relative leniency faced by an inventor who files patent application j in year t assigned to examiner k within art unit a. For a single patent application, the corresponding examiner relative leniency, $E_{jkat} - U_{jat}$, is a suitable instrument for whether that application is granted. However, we are interested in obtaining an instrument for the inventor's total number of applications granted up to a given time. We account for this by averaging $E_{jkat} - U_{jat}$ across all patents applied for by inventor i up to year t:

$$L_{it} = \frac{1}{n_{it}} \sum_{j=1}^{n_{it}} (E_{jkat} - U_{jat}). \tag{3.4}$$

Thus, unlike the previous literature using examiner leniency as an instrument, our study averages leniency at the inventor level. This prevents us from using within-art-unit technology fixed effects in our main specifications. In Appendix B.2, we provide some evidence suggesting

[12]Given that there may be concerns about measurement error in leniency when the set of applications is small, we define some threshold values (10, 20, and 50) and experiment with considering only cases for which the number of reviewed applications per examiner, year and art unit exceeds these thresholds. If anything, results are stronger with these restrictions.

[13]Note that our instrument differs from that proposed by Gaulé (2015) in two respects. First, while the author considers the overall approval rate of an examiner, we follow Sampat and Williams (2015) and Farre-Mensa, Hegde, and Ljungqvist (2017) in adjusting for each art unit. Our reason for doing so is that in our sample period, on average, 39% of examiners reviewed patent applications for multiple art units in the same year. Second, our equations differ in the denominator, since we use the number of patent applications reviewed rather than the number of applications filed. Nothing hinges on the use of the leniency measure in Gaulé (2015), however.

that this is not a concern.

3.5 Patent grants and inventor mobility

3.5.1 Descriptive statistics

Table 3.1 provides descriptive statistics for the main variables used in this study. The unit of observation in our analysis is the inventor-application year. Accordingly, the figures indicate that, on average, 11% of inventors change employers between two application years. Inventors are, on average, responsible for 2.2 granted patents.

Table 3.1
Descriptive statistics

Variable	Mean	SD	Min	Median	Max	Observations
Move	0.11		0	0	1	131,485
# of patents issued	2.2	3.7	0	1	136	131,485
# of applications filed	7.7	11.1	1	4	305	131,485
Examiner leniency	0.004	0.09	-0.86	0.01	0.74	131,485
Years since 1st decision	3.0	2.0	1	2	11	131,485
# of co-inventors	11.0	12.4	0	7	226	131,485
# of uspc classes	2.9	2.4	1	2	49	131,485
% of applications in firm's core	0.30	0.39	0	0	1	131,485
# of applications per firm	1,263	1,776	1	449	7,803	131,485
Enforceability index	-0.72	1.7	-4.2	-0.07	1.6	47,611

3.5.2 Baseline specification

Table 3.2 provides the main results. In column 1, we begin with the OLS estimates of the baseline specification relating mobility to the number of patents granted and additional controls. We find a weak, positive and significant correlation between patent grants and mobility. This relationship cannot be interpreted as causal, however. As argued above, there are reasons why we should expect unobservable factors to affect both the extent to which inventor's patent applications are approved by the USPTO and subsequent mobility.

Moving to the instrumental variable approach, column 2 presents the first stage in which we regress the number of patents issued on *examiner leniency* (and all other controls). As expected, the instrument is positive and highly significant: a one standard deviation increase in the leniency of the examiner assigned to review an inventor's patent application is associated with a seven-percentage-point increase in the number of patents issued for the average inventor. The first-stage F-statistic of the excluded instrument is large (796) and well above the rule of thumb for weak instruments (see, e.g., Stock and Yogo, 2005), indicating that the instrument explains a substantial part of the variation in granted patents. Column 3 reports the result from the second-stage regressions estimating Eq. (3.1), with the main variable of interest replaced with the fitted value of *# of patents issued* from the first-stage regression. The coefficient is strongly negative and significant at the 1% level. The point estimate implies that an exogenous increase in one successful patent application reduces the probability of moving by 2.8%, which represent a 25% decrease over the conditional sample probability of 11%. This is a result of economic significance. The substantial difference between the OLS and IV estimates highlights the importance of controlling for the endogeneity of patent grants and indicates a strong positive correlation between *# of patents issued* and the disturbance in the mobility equation, inducing a large upward bias if we treat USPTO decisions as exogenous.

For the ease of estimation and interpretation, we use linear probability models as our main specifications throughout the paper. In column 4 of Table 3.2, however, we report the results from a probit model where we implement the instrumental variable estimator by using the control function method (see Blundell and Powell, 2004). This leads to qualitatively and quantitatively similar results for the coefficients on *# of patents issued* and, hence, supports the reasonableness of our linear 2SLS model approximations of the average partial effects as suggested, for example, by Wooldridge (2014).

Overall, these instrumental variable specifications provide strong evidence that patents cause, on average, a decrease in the subsequent mobility of early-career inventors. This result suggests that patents make the human capital of inventors more specific to their employers. In the next subsection, we provide a series of robustness checks to address alternative explanations, while in Section 3.6, we provide additional evidence on the heterogeneity of the estimated effect to strengthen our interpretation.

Table 3.2
Patent grants and inventor mobility

	Base	Controlling for endogeneity		
Estimation method	OLS	OLS (1st st.)	2SLS (2nd st.)	Probit (2nd st.)
Dependent variable	Move	# of pats issued	Move	Move
	(1)	(2)	(3)	(4)
# of patents issued	0.001***			
	(0.000)			
Examiner leniency		1.705***		
		(0.060)		
# of patents issued *(instr.)*			-0.028***	-0.022***
			(0.006)	(0.005)
Years since 1st decision (L)	0.038***	1.310***	0.077***	0.069***
	(0.002)	(0.014)	(0.008)	(0.006)
First decision year FE	Yes***	Yes***	Yes***	Yes***
# of applications filed FE	Yes***	Yes***	Yes***	Yes***
Technological class FE	Yes***	Yes***	Yes***	Yes***
First-stage F-statistic		796		

$N = 131,485$. Number of inventors: 69,136. Number of firms: 2,883. Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). Column (4) displays the average marginal effects from a probit model with endogenous regressors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5.3 Robustness checks

In this section, we briefly summarize a variety of tests that allow us to confirm the robustness of our main finding. Results are reported in Appendix B.3.

First, in column 1 of Table B.3, we estimate a specification that incorporates fixed effects at a more fine-grained technology level. In our main specification, we use the six broad (one-digit) NBER technology fields, whereas in this specification we include fixed effects that capture the 37 (two-digit) NBER sub-categories. The estimated coefficient on patent grants is identical to the baseline coefficient.

Second, we check to what extent our estimated coefficient of interest may be subject to attenuation bias. As suggested in Section 3.3, this would be the case if moving inventors were less likely to apply for new patents than stayers. We replicate the main analysis of Table 3.2 for the sub-sample of inventors who obtained at least one decision on their patent applications relatively early in our sample (i.e., prior to 2007). For this group of inventors, the observation window is longer and, therefore, censoring is less likely (we have at least a 5-year time window to observe another application). While 46.2% of first-time inventors are excluded from our main sample because they are only observed once, this percentage is reduced to 26.8% for this sub-sample. The results for this sub-sample are reported in column 2 of Table B.3 and are qualitatively and quantitatively similar to those of our baseline estimatation.

Third, we address the concern that our results could be driven by the sub-sample of inventors whose employers went out of business. If patents affect firm survival (as suggested by Farre-Mensa, Hegde, and Ljungqvist, 2017), we could be detecting purely mechanical moves following inventors' patent rejections (i.e., moves motivated by their employer's bankruptcy). In column 3 of Table B.3, we report the results of a restricted analysis wherein we consider only moves away from source firms that have at least one patent filed in the years after the registered employer change. Restricting the analysis to this sub-set of moves produces nearly identical results to those of our baseline estimation.

Fourth, we examine whether the estimated effect of patent grants on inventor mobility is monotonic. To check this, we include the instrumented squared term of *# of patents issued* in our model. As column 4 of Table B.3 shows, the quadratic term is close to zero and not statistically significant, whereas the linear term remains negative and significant, with a point estimate that is substantially higher than the baseline estimate.

Fifth, one might worry that the effect we observe of patents on mobility is driven by the threat of litigation posed by a few patent holders. As Ganco, Ziedonis, and Agarwal (2015) note, patent holders vary in their toughness for IP litigation, which is correlated with the probability that an inventor exits the firm. To account for this difference, we include the lagged three-year moving sum (i.e., from $t-1$ to $t-3$) of the number of patent infringement lawsuits filed by the focal employer (*Litigiousness*) in the main specification. We obtain this information from the Patent Litigation Docket Reports (publicly available through the USPTO website), which contains all patent litigation cases reported by U.S. district courts to the USPTO between 1963 and 2015. In column 5 of Table B.3, we can observe that the coefficient on *# of patents issued* remains identical to the baseline coefficient, while the coefficient on *Litigiousness* is negative and significant (consistent with prior research). We also interact the effect of patents on mobility with the proxy for IP toughness. In column 6 of Table B.3, we report a negative but non-significant interaction and an estimated coefficient on patent grants of a very similar magnitude to that of the baseline estimate. Hence, patent rights decrease inventor mobility even for employers with low litigation profiles.

Finally, in our last robustness test, we extend the concept of patent protection beyond the granted/non-granted dichotomy and focus on the number of approved claims as a more fine-grained measure of this concept: *the scope of the patent*. Because of our reliance on examiner leniency as an instrumental variable for patent approval, it is likely that the results presented in Table 3.2 represent local average treatment effects of an additional granted patent for the group of inventors producing innovations around the margin of approval and rejection. This analysis of the effect of approved claims allows us to evaluate the effect of a marginal increase in the scope of protection, which may happen at any point on the distribution of patentability. Each claim in a patent document describes in technical terms a different element of the protected technology. As Lanjouw and Schankerman (2001) state, patent claims delimit the boundaries of the legal protection conferred by the patent. A larger set of claims implies that the patent covers a broader share of the technological space. Non-granted patents obviously have no approved claim, and an increasing number of claims implies an increasing scope of protection for the patent holder. The applicant's incentive is to make claims that are as broad as possible in the application, as the examiner can limit these claims during the examination process (Lanjouw and Schankerman, 2001). The scope of patent protection is therefore affected by the examination process and is influenced by examiner leniency. More lenient examiners not only grant more patents but also allow a larger number of claims per patent (Cockburn, Kortum, and Stern, 2003; Lemley and Sampat, 2012). Consequently, examiner leniency can also be used as an instrumental variable to estimate the effect of a broader scope of patent protection on inventor mobility.

Table B.4 presents the estimated effect of the average number of approved claims granted per application on an inventor's likelihood of moving. The number of claims can be readily obtained from patent documents and is available from USPTO datasets. The results are qualitatively similar to those of the analysis of patents granted. Column 2 indicates that examiner leniency is also a strong instrument for approved claims. Column 3 presents the second stage, with a negative and significant coefficient estimate on *Avg. # of claims issued*, suggesting that a one-unit increase in the number of approved claims reduces the probability of moving by 0.3 percentage points – a 2.8% relative decrease in the probability of leaving. To examine the extent to which these results are driven by the fact that non-granted patents have zero approved claims, we repeat the analysis for the sub-sample of granted patents. As the coefficient from the last column of Table B.4 shows, the estimated relationship between approved claims and mobility remains negative and significant.[14] Overall, these results suggest that the main finding of this paper, i.e., the negative effect of patent protection on inventor mobility, is robust to considering the effect of patent scope, a more fine-grained measure of patent protection than patent grants. Consequently, they indicate that the estimated effect is not driven by a subset of inventors whose creations lie around the approval threshold but that it is a more general phenomenon.

[14]The results from this last piece of evidence, however, have to be interpreted with caution, since excluding inventors without granted patents from the analysis is likely to induce some sample selection bias.

3.6 Heterogeneous impact of patent grants

The previous section documents a negative effect of patent protection on inventor mobility, which is consistent with the idea that patent rights make the human capital of inventors specific to their employers. In this section, we explore several sources of heterogeneity in the relationship between patent grants and mobility in order to evaluate the existence of further evidence supporting that proposition. We first examine variations in the effect across technology areas. By drawing on the distinction between discrete and complex technologies outlined by the existing literature, we assess whether the negative effect of patenting on mobility is more pronounced for discrete technologies, where patents arguably provide stronger protection. Second, we explore the role of different sources of firm specificity affecting an inventor's stock of human capital. We examine whether in such cases patents play a less important role as a mechanism that turns inventor's knowledge into firm-specific capital and, thus, affect mobility less intensely. Finally, we examine whether patenting makes an inventor especially less likely to move to firms that are technologically similar to her current employer.

3.6.1 Variation across technology fields

Our argument is that the negative effect of patents on mobility presented in the previous section should be particularly strong in contexts where patents are more effective. The traditional dichotomy between complex and discrete technologies is particularly useful in this respect. Mansfield (1986) and Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches (1987) find that patenting is a key strategy for appropriating returns to R&D in pharmaceuticals and chemicals, while it is less important in most other industries. Cohen, Nelson, and Walsh (2000) push this issue further and suggest that these differences are linked to the nature of the technology and to the physical characteristics of the products. Their rationale is that the number of patentable elements in a product importantly affects the way patents are used and, in turn, the degree to which they contribute to effective protection. In discrete industries, new products typically build on a few clearly identifiable features. Hence, only one or a few patents are required to achieve effective protection against imitation. This is the case in the pharmaceutical and chemical industries, where compounds are typically adequately protected by single patents. In contrast, new products in complex industries, such as electronics, require inputs from numerous complementary components, typically protected by patents held by an array of third parties. This makes the protection conferred by a single patent on a new component inherently less valuable, since it is necessary to have or acquire the rights on other proprietary elements to bring a new product to market. For these reasons, patents are reported to be less effective against imitation in complex product industries relative to alternatives such as secrecy, lead time or complementary capabilities (Cohen, Nelson, and Walsh, 2000).[15] Therefore, we should observe that the negative impact of patents on inventor mobility is stronger in discrete (compared to complex) technology fields.

[15] This claim is also line with the results of econometric studies that attempt to quantify the private value of patent protection across sectors (see, e.g., Lanjouw, 1998; Arora, Ceccagnoli, and Cohen, 2008).

In order to empirically identify the technology field for each patent application, we rely on the NBER categorization. As there is no widely accepted classification that links those categories to discrete or complex technology areas, we focus on the clear-cut cases identified in the prior literature. Following Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches (1987) and Cohen, Nelson, and Walsh (2000), we classify chemicals (category 1) and drugs (sub-category 31) as discrete and computers and communications (category 2), medical instruments (sub-category 32), biotechnology (sub-category 33) and electric and electronics (category 4) as complex technology fields.[16] We then aggregate this information at the inventor–application year level and construct two time-variant dummy variables, *Discrete* and *Complex*, that equal one if the inventor's largest share of applications up to spell t belongs to discrete or complex technology classes, respectively, and zero otherwise.[17] In our sample, the average mobility rate between two application years is 13% for inventors in discrete areas and 10% for those in complex areas.

Table 3.3
Patent grants, technological areas and inventor mobility

Estimation method: 2SLS				Discrete and
Sample	All	Discrete	Complex	complex
Dependent variable: Move	(1)	(2)	(3)	(4)
# of patents issued *(instr.)*	-0.027**	-0.054***	-0.022**	-0.020**
	(0.011)	(0.014)	(0.009)	(0.009)
# of patents issued	-0.026			-0.034*
× Discrete *(instr.)*	(0.018)			(0.019)
# of patents issued	0.008			
× Complex *(instr.)*	(0.014)			
Discrete	0.070**			0.063*
	(0.032)			(0.035)
Complex	0.008			
	(0.029)			
N	131,485	23,991	88,260	110,330
# of inventors	69,136	13,632	46,498	58,296
# of firms	2,883	1,277	1,823	2,523
Wald χ^2	2.96*			

Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). All regressions control for the number of years since inventor's first decision (log), as well as fixed effects for the number of applications filed by the inventor and the year of inventor's first decision. Wald tests for differences in coefficients between *# of patents issued x Discrete* and *# of patents issued x Complex*. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We examine the impact of patents on mobility by technology field using the instrumental variable discussed above. Column 1 of Table 3.3 provides the estimates obtained using the full sample. Specifically, we augment Eq. (3.1) by including two instrumented interaction terms

[16] Traditionally, biotechnology was classified as discrete due to its intrinsic technological characteristics. However, the possibility of patenting gene fragments since the late nineties contributed to the fragmentation of the patent rights needed for the commercialization of a product in this area (Cohen, Nelson, and Walsh, 2000). Thus, following recent papers, such as Galasso and Schankerman (2015), we classify biotechnology as complex. The results are robust to the exclusion of biotech as a complex field.

[17] Because some technological areas are neither complex nor discrete, some 19,234 inventor-year observations are not assigned to either category.

to capture how different appropriability regimes alter the effect of patents on inventor mobility. The coefficient on the first interaction term, *# of patents issued x Discrete*, is large and negative, while that of *# of patents issued x Complex* is small and positive, although neither is statistically significant. The corresponding Wald test indicates, however, that these two coefficients are statistically significantly different from one another. These findings indicate, as predicted, that the negative effect of patents on inventor mobility is stronger when inventors' patent filings are concentrated in discrete technologies instead of complex fields. Columns 2 and 3 present the results of estimating our baseline 2SLS model separately for the subsamples of inventors working mainly in complex technologies and those working mainly in discrete fields. The results show that the effect of patent grants is large, negative and significant among inventors whose main expertise lies in a discrete technology field, whereas it is smaller among inventors in complex areas. One additional patent granted is expected to reduce the probability of moving by 2.2% for inventors in a complex field (a 22% decrease over the conditional sample probability of 10%) and by 5.4% for those in a discrete field (a 42% decrease over the conditional sample probability of 13%). Finally, column 4 provides estimates using the combined sub-samples and interacting *# of patents issued* with *Discrete*. Consistent with the previous findings, the coefficient on the interaction term is negative and significant at the 10% level.

3.6.2 Other sources of firm-specific human capital

A second analysis considers the extent to which different sources of an inventor's firm-specific human capital shape the effect of patents on mobility. In particular, our arguments suggest that the effect will be less negative when other types of human capital firm specificity are already in place, and it will be more intense otherwise. To explore this question, we look at cases in which the inventor's knowledge becomes more valuable when implemented in collaboration with that of other inventors in the company or in conjunction with some of the current employer's key assets. We also analyze whether the effect of patents is attenuated in the presence of another legally induced source of firm specificity: non-compete covenants.

In the context of innovation studies, the literature suggests two potential sources of firm specificity for inventors' human capital. First, Hayes, Oyer, and Schaefer (2006) argue that firm specificity derives from complementarities with the firm's other workers. In particular, by learning to work with each other over time, individual employees develop a stock of human capital that is specific to co-workers and difficult to re-build with others. In the context of invention generation, Jaravel, Petkova, and Bell (2015) show that inventors who experience an unexpected death of a co-inventor face large and long-lasting losses in earnings and productivity. Thus, strong collaborative relationships such as those established in teams of inventors imply that each individual needs complementary knowledge from other inventors to extract the maximum value of her own knowledge. This makes departure decisions more costly for the inventor and reduces her relative attractiveness to outside employers, since competitors that aim to replicate a body of knowledge must hire away the whole team (Palomeras and Melero, 2010). Therefore, we expect the negative impact of patent grants on mobility to be more intense for solo inventors than for inventors with many co-authors.

A second source of firm-specific human capital is suggested by Lazear (2009), who notes that most specific human capital is, in fact, a combination of general purpose skills applied in a combination that is specific to the firm. Innovative companies tend to establish technological trajectories linked to their core competences, with accompanying patterns of standardized routines and procedures (Nelson and Winter, 1982; Hoetker and Agarwal, 2007). This implies that the particular combination of skills used by inventors working in the company's core areas is especially idiosyncratic to the firm and, therefore, difficult to transfer.[18] Thus, we expect that the negative impact of patent grants on mobility is larger for inventors working outside the firm's core technologies than for inventors employed in the firm's core.

We empirically explore the effects of the above-mentioned sources of firm-specific skills by using the following proxies: (i) the natural logarithm of (one plus) the number of unique co-inventors with whom an inventor has worked in her applications up to t and (ii) the percentage of her patent applications that fall in the firm's core technology areas. Following Song, Almeida, and Wu (2003), we consider a technology area part of the core if its corresponding patent class appears with a frequency greater than 10% in the firm's application portfolio (over the entire sample period). We control in these regressions for the inventor's degree of specialization (captured by the number of different patent classes into which her applications fall) and firm size (proxied by the number of applications filed by the firm in that year), which are relevant controls to consistently estimate the effect of co-inventors and core areas.

Table 3.4 presents the results of the interactions between sources of firm specificity and patent grants on mobility. The first column reproduces the baseline model to which we add the variables and controls mentioned in this subsection. We are interested in the interactions between the variables capturing the firm specificity of skills and the number of patents the inventor has been granted. In columns 2 and 3, we add these (instrumented) multiplicative terms separately. Column 4 shows the results for the full model. As expected, the figures from the interaction effects in columns 2 to 4 show that the negative impact of patent grants on mobility is most intense for solo inventors and for inventors working outside the firm's core technologies.

[18] The firm specificity of core skills is illustrated by the following example. In 1970, Intel planned to invest in developing the first semiconductor DRAM (dynamic random access memory), the 1-kilobit 1103. Despite its economic attractiveness, Intel's engineers were seriously concerned about the potential negative consequences of developing knowledge and skills specific to DRAM technology. As noted by Gordon Moore, then CEO of Intel, "[t]here was a lot of resistance to semiconductor technology on the part of the core memory engineers. The engineers didn't embrace the 1103 until they realized that it wouldn't make their skills irrelevant" (Cogan and Burgelman, 1989, p. 2-3).

Table 3.4
Patent grants, firm-specific human capital and inventor mobility

Estimation method: 2SLS Dependent variable: Move	(1)	(2)	(3)	(4)
# of patents issued *(instr.)*	-0.030***	-0.072***	-0.046***	-0.075***
	(0.007)	(0.021)	(0.010)	(0.021)
# of patents issued		0.021***		0.015*
× # of co-inventors (L) *(instr.)*		(0.007)		(0.008)
# of patents issued			0.041**	0.035*
× % of applications in firm's core *(instr.)*			(0.018)	(0.018)
# of co-inventors (L)	0.000	-0.043***	0.002	-0.031*
	(0.002)	(0.016)	(0.002)	(0.017)
% of applications in firm's core	-0.045***	-0.044***	-0.123***	-0.112***
	(0.003)	(0.003)	(0.034)	(0.035)
# of uspc classes (L)	-0.022***	-0.017***	-0.009	-0.007
	(0.004)	(0.003)	(0.006)	(0.006)
# of applications per firm (L)	-0.016***	-0.017***	-0.016***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)

$N = 131,485$. Number of inventors: 69,136. Number of firms: 2,883. Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). All regressions control for the number of years since inventor's first decision (log), fixed effects for the number of applications filed by the inventor, the technology field and the year of inventor's first decision. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also consider the role of non-compete contracts as a related mechanism that increases the firm specificity of inventors' human capital. Non-competes are contractual clauses included in labor contracts that explicitly prevent employees from working for a competitor within a certain time window, typically two years, in case of termination of the labor relationship with the current employer. These covenants are a particular case of trade secret law, which aims to safeguard critical information (both technical and non-technical) that firms decide to keep secret. Non-compete contracts are prevalent among R&D workers and have been found to reduce inventor mobility in states that enforce them (Marx, Strumsky, and Fleming, 2009). U.S. jurisdictions, however, differ in their degree of enforcement of these covenants. Courts have often understood that employees cannot be forbidden to seek jobs in the industry in which they have expertise. In California, for instance, non-competes are practically unenforceable (Gilson, 1999). Thus, the substitutability argument suggests that patents should discourage mobility, especially in states in which non-compete covenants are not enforced.

To examine whether our results differ according to the level of enforcement of non-competes in the corresponding state, we rely on the enforceability index compiled by Starr (2016). We use the inventor address provided in patent filing for the geographical allocation of inventors to U.S. states. Because this information is not available for all inventors in our dataset, we examine a sub-sample of 25,439 inventors from 1,511 firms.

Table 3.5
Patent grants, non-compete enforceability and inventor mobility

Estimation method: 2SLS					Non-enforcing	Enforcing	
Sample	All	All	All	All	states	states	All
Dependent variable: Move	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# of patents issued *(instr.)*	-0.034***	-0.034***	-0.034**	-0.034**	-0.045**	-0.031**	-0.043***
	(0.011)	(0.011)	(0.015)	(0.015)	(0.021)	(0.013)	(0.002)
# of patents issued			0.001	0.002			
× Enforceability index *(instr.)*			(0.005)	(0.005)			
Enforceability index		-0.009***	-0.010				
		(0.003)	(0.013)				
# of patents issued							0.011
× Enforcing states *(instr.)*							(0.014)
Enforcing states							-0.072**
							(0.036)
State FE				Yes***			
N	47,611	47,611	47,611	47,611	10,031	37,580	47,611
# of inventors	25,439	25,439	25,439	25,439	5,480	20,152	25,439
# of firms	1,511	1,511	1,511	1,511	635	1,183	1,511

Estimation period is 2001 – 2011. Robust standard errors are clustered at the state level (in parentheses). All regressions control for the number of years since inventor's first decision (log), fixed effects for the number of applications filed by the inventor, the technology field and the year of inventor's first decision. Enforceability scores for each state are from Starr (2016). Non-enforcing states are California and North Dakota. Since non-competes are enforceable in the state where the employee is located, we use information on inventor's location from the last patent application prior to observing the outcome. Since this information is not available for all inventors, the number of observations is lower in this analysis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In column 1 of Table 3.5, we re-estimate Eq. (3.1) on this sub-sample. The coefficient on *# of patents issued* is -0.034 and significant at the 1% level. In column 2, we add the enforceability index, and we observe that mobility rates decline with the strength of non-compete enforcement, as in Marx, Strumsky, and Fleming (2009). In columns 3 through 7, we then re-estimate the effect of patent grants on mobility by including their interaction term (and state-level fixed effects) and splitting the sample into clearly non-enforcing states (i.e., California and North Dakota) and the rest. Though the effect on mobility is lower in magnitude for enforcing states than for non-enforcing ones, the difference (as captured by the interaction terms) is not significant.

In sum, the evidence presented in this section regarding the relationship between patent rights and other sources of firm-specific human capital is not conclusive. While patent protection has the strongest effect as a retention mechanism for inventors without many co-authors and inventors outside the technological core of the company, we do not observe a similar substitutability pattern between patents and non-compete contracts.

3.6.3 Similarity between hiring and focal firms

Our last test of heterogeneous effects concerns different types of inter-firm moves. The complementarity of patent rights with the human capital of the corresponding inventors is expected to affect all type of moves. However, the appropriation effect resulting from the impact of patent rights on the balance of incentives to hire or retain inventors will only be relevant for technologically similar firms capable of implementing the innovation. Thus, the negative effect of patent grants on mobility observed in this study should more intensely affect moves to alternative employers in the technological vicinity of the current employer than moves to technologically distant firms, which have little chance of implementing an inventor's innovations.

To test this prediction, we characterize inter-firm technological similarity using a measure that captures whether the hiring and focal firms overlap in terms of core technologies. Using the same definition of a firm's core technology area used in Section 3.6.2, we create a categorical variable that is set to 0 when the inventor stays at the focal firm, to 1 when she leaves and at least one core technology domain of the firms is identical; and to 2 when she leaves and there is no overlap in core areas. We then estimate a multinomial logit model that allows us to capture the effect of patent grants on the relative probability of each type of move.[19] Table 3.6 shows the relative risk ratios that result from the analysis. As the first two columns show, one additional patent issued reduces the relative risk that an inventor moves to both technologically overlapping and non-overlapping employers with respect to the omitted "stay" option (both relative risks are multiplied by a factor smaller than one after a patent grant). This is consistent with the complementarity effect of patents on inventor mobility, which drives down the probability of all types of moves. A comparison of the size of the estimated ratios suggests, as predicted, that the effect is more intense for moves to employers with overlapping core technologies than for all other employers. The last column of Table 3.6 shows the relative risk ratios corresponding to the choice between the two types of moves, with moving to employers with no core technological overlap as the reference category. As expected, the figures indicate that an additional patent grant significantly decreases the relative risk that a moving inventor switches to a technologically similar employer instead of switching to an unrelated one.[20] This is consistent with the existence of an appropriation effect that concerns exclusively technologically close employers.

Table 3.6
Technological core of the hiring and the inventor's previous firm

	Core Move Versus Stay	Non-core Move Versus Stay	Core Versus Non-core Move
Dependent variable			
Estimation method: Multinomial Logit	(1)	(2)	(3)
# of patents issued *(instr.)*	0.694***	0.849***	0.816**

$N = 131,485$. Number of inventors: 69,136. Number of firms: 2,883. Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). All regressions control for the number of years since inventor's first decision (log), fixed effects for the number of applications filed by the inventor, the technology field and the year of inventor's first decision. Coefficients are expressed in terms of relative risk ratios. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[19] Again, we used the control function approach proposed by Blundell and Powell (2004) and Wooldridge (2014) to correct for the endogeneity of issued patents with the average examiner leniency instrument in the multinomial logit model.

[20] In unreported extensions, we distinguish between a hiring firm whose core technology overlaps with the mobile inventor's own technological expertise (instead of her previous employer's core technology) to categorize moves. Replicating the specification of Table 3.6 for the alternative categorization produces similar results to those presented here.

3.7 Discussion and conclusion

In this study we investigate the effect of patent protection on the mobility prospects of an inventor. We argue that, by making the inventors knowledge more specific to their current employers, patent grants decrease inter-firm mobility.

In order to test this idea, we examine the impact of obtaining a patent on the mobility patterns of the inventors involved in applications. Since inventions that are granted and not granted patents are expected to be inherently different, we adopt an instrumental variables approach to estimate the effect of patenting on inventors' mobility. In particular, and following previous literature, we use variations in the granting rates of patent examiners within an art unit (leniency). We analyze the early careers of inventors employed at firms who apply for patents in the USPTO for the first time between 2001 and 2012. Our results indicate that patenting does cause a substantial decrease in the mobility of inventors in their early careers, suggesting that patent grants make human capital more specific to the inventor's current employer. Additional evidence provides further support for this hypothesis: (i) the negative effect of patents on mobility is particularly strong in discrete technologies, where patent protection is more effective, (ii) patents have a less negative effect on mobility when other sources of firm specificity are present. In particular, complementarities with co-inventors and employer's assets make an inventor's knowledge set more difficult to transfer outside the company, and (iii) patents make inventors especially less likely to move to technologically close alternative employers (compared to technologically distant ones). Among other robustness tests, we address external validity concerns by extending the concept of patent protection from patent grants to the number of approved claims. The results of this analysis suggest that the appropriation effect is present over the whole population of patent applicants and not only for those producing innovations in the margin of approval and rejection.

One feature of our research design is that it does not allow us to capture the role of patents as signals of inventor ability. Previous findings in the labor economics and innovation literatures suggest that patents could reveal information about inventive skills. Patents have been frequently argued to work as signals of firm quality in situations of asymmetric information in entrepreneurial finance markets (Long, 2002; Hsu and Ziedonis, 2013; Conti, Thursby, and Thursby, 2013). Analogously, patents could act as signals in the labor market for highly skilled employees, where employers are particularly likely to enjoy private information about the ability of their workers (Schönberg, 2007). By providing a signal to the labor market about the quality of the inventors responsible for the innovation, patent documents could decrease the amount of private information held by current employers and thus increase inventor mobility. Our empirical strategy, however, is based on a comparison of patent filings that have been granted and those that have not. Since the immense majority of filings are public, we would expect signaling effects to be mainly associated to patent application events and not to grant events. Indeed, it is at the time of the publication of the application when the information about the innovation and its inventors is released to the market. Thus, it is conceivable that the negative effect of patent grants on inventor mobility is preceded by a positive effect of applications.

Notwithstanding the previous caveat, the evidence presented in this paper indicates that patent protection makes the human capital of inventors more firm specific and, therefore, lowers the likelihood of moving. This result has important public policy implications. First, it suggests that patents, despite making public some codified knowledge, may have a growth-reducing effect by hampering the diffusion of tacit know-how. By inducing lower mobility rates, they may reduce the spread of non-codified knowledge associated with the protected technology and, more generally, of other know-how not related to the replicability of a specific innovation. Furthermore, this appropriation-induced reduction in mobility may also contribute to an inefficient allocation of inventor's skills. Evidence from Hoisl (2007) shows that inventors tend to experience productivity increases when they switch firms, suggesting that career moves are frequently motivated by employer-employee match improvements. To the extent that patents discourage mobility, they will also inhibit these efficiency improvements. Finally, our results also suggest that patents generate a shift in incentives to invest in human capital from the employees (i.e., the inventors) to their employers (i.e., the patent holders). This shift may encourage some efficient investments in training that might not have been otherwise carried out by the inventors themselves because of financial constraints or risk considerations.

In terms of managerial implications, our results suggest that inventors may not have strong incentives to generate patentable innovations if patents decrease their outside options due to the appropriation effect. In that case, firms that rely on patent protection should complement that strategy with an internal incentive system that rewards patents (as documented by Toivanen and Väänänen, 2012).

Last but not least, our findings bring to light an important methodological issue. If patent grants affect the mobility prospects of the authors of the inventions, tracking inventors' careers through their issued patents (as most studies have done until now) introduces a downward bias in the detection of mobility. This bias may expand to analyses of causes and consequences of mobility as well. To avoid it, further studies at the inventor level should take into account both patent applications and grants.

Appendix A

Appendix for "The Bright Side of Financial Derivatives: Options Trading and Firm Innovation"

This Appendix provides additional material to the results presented in *"The Bright Side of Financial Derivatives: Options Trading and Firm Innovation."* In Section A.1, we describe the construction of the main data set. In Section A.2, we discuss and report robustness checks for the baseline results reported in Section 2.4 of the paper. In Section A.3, we report additional tests that supplement other parts of the main article. Descriptive statistics are in Table A.16.

A.1 Main data set

The main firm-level data sample is generated through the combination of several data sets. Because we are using patents (weighted by total future citations) as our key measure of innovation, we rely on the matching of the United States Patent and Trademark Office (USPTO) to the North American Compustat data hosted at the National Bureau of Economic Research (NBER) (see Hall, Jaffe, and Trajtenberg, 2001; Jaffe and Trajtenberg, 2002, for details). The main matching was performed based on the concordance file provided by Bessen (2009) that connects the assignee identification number of the NBER patent data set to the Compustat GVKEY identification number. These connections reflected the firms and subsidiaries identified in the Who Owns Whom? database (published annually by Dun & Bradstreet International). Ownership may change through mergers, acquisitions, or spin-offs, and when an organization is acquired/merged/spun-off, its patents likely transfer to the new owner. These changes have been tracked using data on the mergers and acquisitions of public companies reported in the SDC database. We use the updated version of the NBER match containing citations through 2006 (downloaded from the NBER Patent Data Project website, https://sites.google.com/site/patentdataproject). All patents granted between 1976 and 2004 are included (just under three million patents), and citation information is available from 1976 to 2006 (over 23 million citations). The need to have some patent data is the main reason that our sample is considerably smaller than the full Compustat sample.

The second data set we draw on comes from OptionMetrics LLC, a financial research firm specializing in the analysis of option markets. The IvyDB U.S. data set from OptionMetrics contains daily closing option prices (bid and ask) for all U.S. exchange-listed and Nasdaq equities and market indexes, as well as all U.S.-listed index and equity options, starting from January 1996 (which is why this is the first year in our sample). In addition to option prices, it also contains daily time-series of the underlying spot prices, dividend payments and projections, stock splits, historical daily interest rate curves and, most important, option volumes. Implied volatilities and sensitivities (delta, gamma, vega, and theta) for each option are also calculated. The comprehensive nature of the database makes it most suitable for empirical work on option markets. The primary key (Security ID) for all data contained in IvyDB is linked to the security's CUSIP number and ticker symbol, and hence merging the two data sets is straightforward.

Third, we obtain data on institutional ownership from Thomson Reuters' CDA/Spectrum Institutional Holdings data set. Starting in 1978, all institutions with more than $100 million in securities under discretionary management have been required to report their holdings to the Securities and Exchange Commission (SEC) using Form 13F. Each quarter, these institutions must disclose any common stock positions greater than 10,000 shares or greater than $200,000 in value. The data include the number of institutional owners, the number of share issues, and the percentage of outstanding shares held by each institution. For each fiscal year, we take the average of the four quarterly institutional holdings given by Form 13F and treat that as our measure of institutional ownership (*InstOwn*). As the ownership data do not cover all the firms in the data set, we lose 304 firms when we match the Compustat accounting data and ownership data.

We began with the NBER USPTO/Compustat match and kept all domestic firms trading on NYSE (stock exchange code 11), Amex (12) and Nasdaq (14) with non-missing accounting data on fixed assets (PPENT), employees (EMP), and sales (SALE) that are listed on Compustat for at least three years. As our preferred regressions use fixed effects, we condition our sample on firms that had received at least one citation and had at least two years of non-missing data on all variables. This leaves us with a merged data set of 1,329 firms and 9,265 observations between 1996 (the first year of the options data) and 2004 (the last year of the patent data). For reasons explained in the main article, our final sample consists of firms with positive options volume that are active in five broadly defined R&D-intensive industries: (i) pharmaceuticals (SIC code 283), (ii) industrial and commercial machinery and computer equipment (35), (iii) electronics and communications (36), (iv) transportation equipment (37), and (v) instruments and related products (38). This leaves us with 3,271 observations on 548 firms, which is our baseline sample.

A.2 Robustness tests for the baseline results

We conduct a rich set of robustness checks of our baseline results and report them in Tables A.1 – A.11. First, we check whether our results are robust to alternative econometric models. We begin with a Poisson model where the dependent variable is the number of cite-weighted patents and the number of (unweighed) patents and report the results in Table A.1. The coefficients on *Ln(Optvol)* remain positive and significant across all columns, consistent with our baseline findings. For example, the coefficient estimate on *Ln(Optvol)* is 0.143 (p-value < 0.01) if we reproduce our baseline fixed effects model of cite-weighted patents (column 4 of Table 2.2 in the main article) and is 0.106 (p-value < 0.05) when we use simple patent counts as the dependent variable. Next, because our dependent variables are right-skewed (e.g., 24% of our firm-year observations have zero citations), we use three modeling strategies that take this into account. We report the results in Table A.2. In columns 1 and 2, we adopt a quantile regression approach at the 75$^{\text{th}}$ percentile. The baseline results continue to hold, and we obtain similar findings if we run the quantile regressions at the 70$^{\text{th}}$, 80$^{\text{th}}$, 85$^{\text{th}}$, and the 95$^{\text{th}}$ percentiles. We then use zero-inflated negative binomial (columns 3 and 4) and zero-inflated Poisson models (columns 5 and 6). We also find consistent results.

Second, because our main analysis uses contemporaneous independent variables, we run alternative specifications where we lag the variables. As a first step, our approach was to empirically explore the effects of time lags between options trading and the dependent variables. Estimating models with various time lags (i.e., from $t-1$ to $t-5$) for the options trading variable, we found broadly consistent results for all models, but with coefficients on *Ln(Optvol)* that were consistently larger than those obtained from the contemporaneous models. We present the results of models with one- and three-year lagged explanatory variables, as adding further lags reduces the number of observations for firms in the data set, without providing any appreciable gain in the precision of the estimates. The coefficients on *Ln(Optvol)* are shown in Panels A (one-year lag) and B (three-year lag) of Table A.3, and are positive in all regressions. For example, the coefficients in column 1 suggest that increasing options trading activity from the sample median ($8.5 million) to the 75$^{\text{th}}$ percentile ($53.5 million) is associated with a 98% increase in future cite-weighted patents in the following year and a 67% increase in three years, all significant at the 1% level.

Third, we examine whether the effect of options volume on innovation is monotonic (i.e., after conditioning on covariates). In Table A.4, we begin with the inclusion of *Ln(Optvol)* and its squared term. We find that the impact of *Ln(Optvol)* on cite-weighted patents remains positive and significant (coefficient = 0.105 and p-value < 0.1 in column 1 of Table A.4), but the coefficient estimate on the squared term, *Ln(Optvol) x Ln(Optvol)*, is not significant. Next, we create a dummy variable, *High Optvol*, that equals one if the options volume for a given firm is above the median in that year and zero otherwise and interact this dummy with *Ln(Optvol)*. We then re-estimate Eq. (1) in the main article by adding the *High Optvol* dummy and the interaction term, *Ln(Optvol) x High Optvol*. However, as shown in columns 2, 4, and 6, the coefficient estimates on the interaction terms are not statistically significant, while the coefficients on *Ln(Optvol)* remain positive and highly significant. In untabulated analyses, we obtain similar results if we replace the dependent variable with unweighted patent counts. Overall, and consistent with the bivariate relationship in Fig. 2.1 in the main article, it appears that the effect of options trading activity on innovation is monotonic.

Fourth, our preferred control for R&D inputs is a continuous measure of the depreciated sum of past R&D expenditures. Although widely used in prior studies, it may partly conceal some of the effects of R&D. To mitigate such concerns, we include only the contemporaneous R&D flow and establish dummy variables based on deciles of the distribution of *R&D stock*. We report the results in Tables A.5 and A.6, respectively. In both cases, the coefficients on options volume continue to be positive and significant. For example, according to columns 1 and 2 of Table A.5, an increase in options volume from the sample median (\$8.5 million) to the 75$^{\text{th}}$ percentile (\$53.5 million) is associated with a 74% increase in citations and a 74% increase in the number of patents filed.

Fifth, as our sample period (1996 – 2004) includes the "dot-com bubble," which is conventionally dated between 1996 and 2000, we rerun our regressions for the two subperiods 1996 – 2000 and 2001 – 2004. As Table A.7 shows, the coefficients on *Ln(Optvol)* are positive and significant (at the 1% level) in both subperiods, which provides reassurance that our results are not driven by high coefficient magnitudes in the earlier or later periods.

Finally, in Table A.8, we report the regression results after the inclusion of additional (financial) control variables. In Table A.9, we report the regression results after controlling for firms' external knowledge acquisition activities. In Table A.10, we report the regression results on the differential effect of options trading on innovation in R&D- and non-R&D-intensive industries based on a matched sample. In Table A.11, we report the within-firm regression results that compare changes in innovation before and after firms' inclusion in options markets. These findings are discussed in Section 2.4.2 of the main article.

A.3 Other tests

In this section, we present additional regression results that supplement other parts of the paper. We discuss these results in the main text.

In Table A.12, we report the results from the two-stage least-squares regression (2SLS) using the average open interest across all options on a stock throughout the calendar year as an alternative instrument.

In Table A.13, we present the regression results on the interaction between options volume and managerial entrenchment using the "Entrenchment Index" (E-Index) (see Bebchuk, Cohen, and Ferrell, 2009, for details).

In Table A.14, we report the regression results from examining the effect of firm innovation (and options volume) on a firm's market valuation (Tobin's Q).

In Table A.15, we present the regression results from examining the effect of options volume on innovation after controlling for all five economic mechanisms.

Table A.1
Options volume and innovation–Poisson model

Dependent Var.	CITES				PATS			
Method: Poisson	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Optvol)	0.230***	0.139***	0.238***	0.143***	0.132***	0.117***	0.122**	0.106**
	(0.062)	(0.034)	(0.067)	(0.035)	(0.051)	(0.042)	(0.053)	(0.044)
InstOwn	-0.040	-0.088	-0.055	-0.102	-0.189	-0.083	-0.090	-0.054
	(0.240)	(0.221)	(0.219)	(0.215)	(0.237)	(0.235)	(0.223)	(0.222)
Ln(K/L)	0.634***	0.519***	0.676***	0.555***	0.477**	0.371**	0.530***	0.427***
	(0.232)	(0.164)	(0.252)	(0.170)	(0.186)	(0.165)	(0.195)	(0.165)
Ln(Sales)	0.531***	0.250***	0.219*	0.128*	0.610***	0.330***	0.214**	0.148**
	(0.091)	(0.067)	(0.117)	(0.076)	(0.070)	(0.065)	(0.095)	(0.069)
Ln(Age)	-0.042	-0.261**	-0.175*	-0.330***	-0.014	-0.255**	-0.191**	-0.352***
	(0.110)	(0.112)	(0.102)	(0.099)	(0.086)	(0.109)	(0.086)	(0.093)
Ln(R&D stock)			0.349**	0.165*			0.469***	0.275***
			(0.138)	(0.090)			(0.109)	(0.091)
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,271	3,271	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. The time period is 1996 – 2004 (with citations up to 2006); fixed effects are based on including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2
Options volume and innovation–Other (alternative) specifications

Method	Quantile regression		Zero-inflated NB		Zero-inflated Poisson	
Dependent Var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.105***	0.106***	0.164***	0.142***	0.155***	0.115**
	(0.016)	(0.013)	(0.028)	(0.024)	(0.040)	(0.049)
InstOwn	-0.034	-0.153*	0.046	0.102	-0.088	0.004
	(0.128)	(0.088)	(0.164)	(0.175)	(0.211)	(0.218)
Ln(K/L)	0.021	0.032	0.167**	0.182***	0.564***	0.449***
	(0.052)	(0.036)	(0.070)	(0.060)	(0.168)	(0.163)
Ln(Sales)	0.123***	0.118***	0.108***	0.138***	0.114	0.137**
	(0.025)	(0.021)	(0.038)	(0.043)	(0.074)	(0.068)
Ln(Age)	-0.167***	-0.082*	-0.215**	-0.235***	-0.318***	-0.356***
	(0.060)	(0.044)	(0.087)	(0.076)	(0.097)	(0.092)
Ln(R&D stock)	0.315***	0.262***	0.285***	0.266***	0.163*	0.276***
	(0.030)	(0.025)	(0.039)	(0.044)	(0.088)	(0.089)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of quantile (at the 75$^{\text{th}}$ percentile), zero-inflated NB, and zero-inflated Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors in columns 1 and 2 are obtained from 200 bootstrap replications. All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3
Options volume and innovation–Lagged explanatory variables

Method	OLS		NB		Poisson	
Dependent var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: One-year lag						
Ln(Optvol)	0.185***	0.179***	0.181***	0.152***	0.146***	0.123**
	(0.033)	(0.028)	(0.033)	(0.027)	(0.047)	(0.056)
InstOwn	-0.108	-0.215	0.002	0.025	-0.103	-0.024
	(0.182)	(0.162)	(0.202)	(0.172)	(0.215)	(0.204)
Ln(K/L)	0.023	0.042	0.078	0.151**	0.610***	0.463***
	(0.060)	(0.050)	(0.079)	(0.067)	(0.191)	(0.170)
Ln(Sales)	0.123***	0.126***	0.132***	0.152***	0.147	0.170**
	(0.044)	(0.036)	(0.043)	(0.040)	(0.090)	(0.072)
Ln(Age)	-0.116	-0.059	-0.215**	-0.258***	-0.353***	-0.385***
	(0.090)	(0.077)	(0.100)	(0.082)	(0.104)	(0.091)
Ln(R&D stock)	0.255***	0.200***	0.311***	0.265***	0.146	0.242**
	(0.050)	(0.046)	(0.047)	(0.045)	(0.105)	(0.101)
Observations	2,658	2,658	2,658	2,658	2,658	2,658
Panel B: Three-year lag						
Ln(Optvol)	0.130***	0.179***	0.138***	0.164***	0.157***	0.132**
	(0.042)	(0.039)	(0.044)	(0.033)	(0.049)	(0.061)
InstOwn	-0.058	-0.194	0.142	0.027	-0.064	0.099
	(0.222)	(0.201)	(0.243)	(0.192)	(0.265)	(0.213)
Ln(K/L)	0.005	0.048	0.179**	0.143**	0.733***	0.578***
	(0.068)	(0.062)	(0.084)	(0.070)	(0.222)	(0.174)
Ln(Sales)	0.159***	0.158***	0.186***	0.167***	0.153	0.205***
	(0.047)	(0.042)	(0.054)	(0.042)	(0.115)	(0.076)
Ln(Age)	-0.099	-0.105	-0.211*	-0.294***	-0.409***	-0.452***
	(0.099)	(0.091)	(0.112)	(0.083)	(0.120)	(0.092)
Ln(R&D stock)	0.215***	0.170***	0.259***	0.236***	0.118	0.182*
	(0.051)	(0.051)	(0.053)	(0.048)	(0.122)	(0.105)
Observations	1,687	1,687	1,687	1,687	1,687	1,687

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on (lagged) options volume (*Optvol*) and other (lagged) firm-level control variables. Firms in all columns: 526 in Panel A and 399 in Panel B. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4
Options volume and innovation–Monotonic relationship?

Method	OLS		NB		Poisson	
Dependent Var.	Ln(1+CITES)	Ln(1+CITES)	CITES	CITES	CITES	CITES
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)		0.065		-0.012		-0.045
x High Optvol		(0.069)		(0.067)		(0.072)
High Optvol		-0.159		0.042		0.166
		(0.269)		(0.251)		(0.259)
Ln(Optvol)	0.009		-0.003		-0.011	
x Ln(Optvol)	(0.008)		(0.008)		(0.008)	
Ln(Optvol)	0.105*	0.127***	0.176***	0.162***	0.254***	0.184***
	(0.059)	(0.044)	(0.060)	(0.046)	(0.074)	(0.059)
InstOwn	-0.017	-0.024	0.066	0.068	-0.126	-0.103
	(0.159)	(0.159)	(0.178)	(0.178)	(0.222)	(0.222)
Ln(K/L)	0.025	0.024	0.107	0.106	0.540***	0.553***
	(0.052)	(0.052)	(0.067)	(0.067)	(0.172)	(0.172)
Ln(Sales)	0.127***	0.127***	0.135***	0.135***	0.140*	0.128*
	(0.041)	(0.041)	(0.040)	(0.040)	(0.072)	(0.075)
Ln(Age)	-0.107	-0.106	-0.213**	-0.213**	-0.326***	-0.328***
	(0.084)	(0.084)	(0.095)	(0.095)	(0.102)	(0.102)
Ln(R&D stock)	0.253***	0.253***	0.301***	0.300***	0.159*	0.164*
	(0.046)	(0.046)	(0.042)	(0.042)	(0.085)	(0.086)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) on options volume (*Optvol*), its squared term, a dummy variable for high options volume (*High Optvol*), its interaction with options volume, and other firm-level control variables. *High Optvol* equals one if the options volume for a given firm is above the median in year t and zero otherwise. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5
Options volume and innovation–Contemporaneous R&D spending

Method	OLS		NB		Poisson	
Dependent Var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.140***	0.136***	0.133***	0.122***	0.141***	0.091*
	(0.030)	(0.025)	(0.029)	(0.025)	(0.043)	(0.052)
InstOwn	-0.041	-0.218	0.021	-0.032	-0.084	-0.039
	(0.156)	(0.137)	(0.177)	(0.147)	(0.207)	(0.214)
Ln(K/L)	0.026	0.042	0.099	0.141**	0.562***	0.430***
	(0.052)	(0.044)	(0.065)	(0.058)	(0.171)	(0.164)
Ln(Sales)	0.100**	0.095***	0.131***	0.132***	0.078	0.094
	(0.042)	(0.034)	(0.042)	(0.039)	(0.070)	(0.064)
Ln(Age)	-0.040	0.024	-0.144	-0.151**	-0.298***	-0.291***
	(0.082)	(0.067)	(0.093)	(0.075)	(0.109)	(0.103)
Ln(1+XRD)	0.316***	0.256***	0.331***	0.290***	0.224**	0.349***
	(0.052)	(0.046)	(0.048)	(0.047)	(0.093)	(0.084)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), contemporaneous R&D spending (*XRD*), and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6
Options volume and innovation–R&D stock dummy variables

Method	OLS		NB		Poisson	
Dependent Var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.163***	0.145***	0.149***	0.132***	0.147***	0.115***
	(0.029)	(0.024)	(0.028)	(0.024)	(0.032)	(0.043)
InstOwn	-0.088	-0.188	0.073	-0.039	-0.271	-0.187
	(0.166)	(0.140)	(0.176)	(0.146)	(0.217)	(0.220)
Ln(K/L)	0.024	0.035	0.100	0.144**	0.473***	0.381**
	(0.053)	(0.043)	(0.067)	(0.058)	(0.152)	(0.156)
Ln(Sales)	0.105***	0.081**	0.095**	0.093**	0.144**	0.177***
	(0.040)	(0.033)	(0.039)	(0.037)	(0.067)	(0.062)
Ln(Age)	-0.131	-0.067	-0.255***	-0.244***	-0.258***	-0.296***
	(0.083)	(0.067)	(0.095)	(0.075)	(0.094)	(0.096)
R&D stock, 10%	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark
R&D stock, 20%	0.162	-0.096	0.119	-0.125	0.028	-0.259
	(0.145)	(0.090)	(0.161)	(0.132)	(0.187)	(0.220)
R&D stock, 30%	0.533***	0.174*	0.648***	0.332**	0.265	0.172
	(0.145)	(0.099)	(0.160)	(0.132)	(0.191)	(0.229)
R&D stock, 40%	0.648***	0.257**	0.578***	0.423***	0.207	0.323
	(0.154)	(0.113)	(0.168)	(0.137)	(0.199)	(0.237)
R&D stock, 50%	0.793***	0.347***	0.668***	0.621***	0.425**	0.567**
	(0.180)	(0.134)	(0.177)	(0.160)	(0.206)	(0.255)
R&D stock, 60%	0.784***	0.480***	0.887***	0.829***	0.436*	0.638**
	(0.182)	(0.140)	(0.184)	(0.160)	(0.229)	(0.260)
R&D stock, 70%	0.959***	0.635***	1.106***	0.998***	0.625***	0.805***
	(0.192)	(0.155)	(0.201)	(0.170)	(0.231)	(0.265)
R&D stock, 80%	1.259***	0.804***	1.379***	1.135***	0.941***	1.065***
	(0.206)	(0.175)	(0.210)	(0.185)	(0.234)	(0.275)
R&D stock, 90%	1.611***	1.285***	1.881***	1.610***	1.156***	1.438***
	(0.251)	(0.225)	(0.244)	(0.219)	(0.305)	(0.312)
R&D stock, 100%	1.858***	1.613***	2.260***	1.975***	0.966**	1.523***
	(0.316)	(0.302)	(0.296)	(0.284)	(0.383)	(0.376)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*), *R&D stock* dummy variables based on deciles of its distribution, and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7
Options volume and innovation–Internet bubble

Period	"1996 – 2000"			"2001 – 2004"		
Method	OLS	NB	Poisson	OLS	NB	Poisson
Dependent Var.	Ln(1+CITES)	CITES	CITES	Ln(1+CITES)	CITES	CITES
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.176***	0.134***	0.149***	0.161***	0.164***	0.179**
	(0.035)	(0.031)	(0.039)	(0.037)	(0.045)	(0.070)
InstOwn	0.002	0.089	-0.131	-0.303	-0.018	0.179
	(0.188)	(0.170)	(0.209)	(0.185)	(0.280)	(0.443)
Ln(K/L)	0.026	0.086	0.533***	0.048	0.125	0.769***
	(0.066)	(0.072)	(0.170)	(0.060)	(0.098)	(0.224)
Ln(Sales)	0.173***	0.144***	0.127	0.061	0.095	0.049
	(0.049)	(0.042)	(0.078)	(0.042)	(0.065)	(0.088)
Ln(Age)	-0.256***	-0.284***	-0.334***	0.121	-0.026	-0.291*
	(0.096)	(0.091)	(0.097)	(0.098)	(0.137)	(0.176)
Ln(R&D stock)	0.260***	0.291***	0.167*	0.243***	0.372***	0.205**
	(0.054)	(0.040)	(0.094)	(0.049)	(0.075)	(0.101)
Observations	1,906	1,906	1,906	1,365	1,365	1,365

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) on options volume (*Optvol*) and other firm-level control variables for the two subperiods 1996 – 2000 (during the "dot-com bubble") and 2001 – 2004 (after the "dot-com bubble"). Firms in columns: 501 in columns 1 – 3 and 398 in columns 4 – 6. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8
Options volume and innovation–Additional (financial) controls

Method	OLS		NB		Poisson	
Dependent Var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.110***	0.097***	0.118***	0.099***	0.152***	0.104**
	(0.022)	(0.019)	(0.023)	(0.020)	(0.044)	(0.051)
InstOwn	0.005	-0.290	-0.184	-0.212	-0.340	-0.226
	(0.242)	(0.183)	(0.299)	(0.210)	(0.298)	(0.292)
Ln(K/L)	-0.077	0.018	0.041	0.089	0.373***	0.255***
	(0.070)	(0.054)	(0.096)	(0.073)	(0.128)	(0.084)
Ln(Sales)	0.064	0.048	0.069	0.047	-0.177	0.045
	(0.060)	(0.045)	(0.059)	(0.053)	(0.117)	(0.088)
Ln(Age)	-0.041	0.048	-0.097	-0.064	-0.285**	-0.281**
	(0.113)	(0.086)	(0.122)	(0.091)	(0.131)	(0.124)
Ln(R&D stock)	0.274***	0.254***	0.269***	0.304***	0.492***	0.473***
	(0.069)	(0.054)	(0.061)	(0.059)	(0.118)	(0.085)
Illiquidity	-0.109*	-0.136**	-0.173**	-0.162***	-0.088	-0.032
	(0.062)	(0.052)	(0.068)	(0.055)	(0.086)	(0.067)
Leverage	0.548*	0.280	0.500	0.254	0.315	0.003
	(0.296)	(0.229)	(0.338)	(0.236)	(0.402)	(0.451)
Tobin's Q	-0.073	-0.047	-0.135	-0.085	-0.038	0.105
	(0.082)	(0.059)	(0.085)	(0.063)	(0.111)	(0.118)
ROA	-0.553	-0.531**	-0.871**	-0.758***	0.716	-0.205
	(0.373)	(0.251)	(0.361)	(0.286)	(0.449)	(0.448)
Capex	1.613	0.087	-0.344	-0.402	0.564	1.196
	(1.041)	(0.758)	(0.995)	(0.801)	(0.952)	(1.188)
Ln(1+Analyst coverage)	-0.003	0.044	0.029	0.050	0.070	0.039
	(0.080)	(0.064)	(0.083)	(0.064)	(0.073)	(0.058)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other (additional) firm-level control variables. *Illiquidity* is the natural logarithm of the relative effective spread measured over firm i's fiscal year t, where the relative effective spread is defined as the absolute value of the difference between the execution price and the midpoint of the prevailing bid-ask quote divided by the midpoint of the prevailing bid-ask quote; *Leverage* is the book value of debt (DLTT+DLC) divided by the book value of assets (AT); *Tobin's Q* is calculated as (market value of equity (PRCC_F $\times$ CSHO) plus the book value of assets (AT) minus the book value of equity (CEQ) minus balance sheet deferred taxes (TXDB)) divided by the book value of assets (AT); *ROA* is operating income before depreciation (OIDBP) divided by the book value of assets (AT); *Capex* is defined as capital expenditures (CAPX) scaled by the book value of assets (AT); and *Analyst coverage* is the arithmetic mean of the 12 monthly numbers of earnings forecasts for firm i extracted from the I/B/E/S summary file. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9
Options volume and innovation–External knowledge acquisition

Control variable	Collaboration frequency		Collaboration intensity		Acquisitions	
Dependent Var.	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.107***	0.090***	0.116***	0.158***	0.114***	0.156***
	(0.020)	(0.017)	(0.019)	(0.024)	(0.019)	(0.024)
InstOwn	-0.186	-0.252*	-0.164	-0.224	-0.153	-0.211
	(0.152)	(0.139)	(0.153)	(0.141)	(0.152)	(0.139)
Ln(K/L)	-0.012	0.040	-0.011	0.042	-0.014	0.040
	(0.048)	(0.043)	(0.049)	(0.044)	(0.048)	(0.044)
Ln(Sales)	0.129***	0.122***	0.121***	0.111***	0.130***	0.122***
	(0.036)	(0.033)	(0.037)	(0.034)	(0.036)	(0.033)
Ln(Age)	-0.062	-0.032	-0.059	-0.032	-0.057	-0.027
	(0.077)	(0.069)	(0.078)	(0.069)	(0.077)	(0.069)
Ln(R&D stock)	0.250***	0.193***	0.263***	0.210***	0.259***	0.204***
	(0.041)	(0.043)	(0.042)	(0.044)	(0.042)	(0.043)
Collaboration freq.	0.106***	0.129***				
	(0.035)	(0.032)				
Collaboration int.			-0.731*	-0.923***		
			(0.393)	(0.303)		
Acquisitions					-0.570**	-0.539**
					(0.290)	(0.257)
Observations	1,446	1,446	3,271	3,271	3,271	3,271

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*), *collaboration frequency*, *collaboration intensity*, *acquisitions*, and other firm-level control variables. *Collaboration frequency* is the natural logarithm of (one plus) the number of R&D alliances formed over the previous five years (i.e., from $t-5$ to $t-1$); *Collaboration intensity* is the number of a firm's jointly owned patents filed over the previous five years scaled by its total number of patents filed over the same period; and *Acquisitions* is the acquisition expenditure (ACQ) divided by the book value of assets (AT). Firms in columns: 236 in columns 1 and 2; 548 in columns 3 – 6. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10
Options volume and innovation–High- versus low-tech industries

Dependent Var.	Ln(1+CITES)				Ln(1+PATS)			
Matched sample	All	All	High-tech	Low-tech	All	All	High-tech	Low-tech
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Optvol)		0.186***				0.193***		
x Dummy for high-tech		(0.059)				(0.056)		
Ln(Optvol)	0.120***	0.004	0.144***	0.070	0.113***	-0.007	0.147***	0.046
	(0.039)	(0.052)	(0.049)	(0.058)	(0.034)	(0.049)	(0.040)	(0.051)
Dummy for high-tech	1.219**	0.932*			0.543	0.243		
	(0.485)	(0.510)			(0.578)	(0.605)		
InstOwn	-0.092	-0.053	-0.148	0.199	-0.164	-0.123	-0.287	0.208
	(0.189)	(0.188)	(0.248)	(0.252)	(0.170)	(0.170)	(0.231)	(0.216)
Ln(K/L)	-0.068	-0.071	0.085	-0.252*	-0.023	-0.025	0.090	-0.166
	(0.098)	(0.097)	(0.134)	(0.143)	(0.079)	(0.079)	(0.111)	(0.109)
Ln(Sales)	0.104*	0.091	0.180**	-0.076	0.100*	0.086*	0.163**	-0.031
	(0.062)	(0.062)	(0.087)	(0.081)	(0.053)	(0.052)	(0.075)	(0.065)
Ln(Age)	-0.138	-0.150*	-0.155	-0.156	-0.099	-0.111	-0.114	-0.119
	(0.085)	(0.084)	(0.113)	(0.118)	(0.073)	(0.072)	(0.097)	(0.102)
Ln(R&D stock)	0.167***	0.167***	0.212***	0.099**	0.143***	0.143***	0.158***	0.114***
	(0.034)	(0.034)	(0.050)	(0.043)	(0.028)	(0.027)	(0.041)	(0.035)
Observations	2,906	2,906	1,453	1,453	2,906	2,906	1,453	1,453

This table presents estimates of OLS panel regressions on a matched sample of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume *(Optvol)*, a dummy variable that equals one if a firm is operating in a high-tech industry (*Dummy for high-tech*), their interaction, and other firm-level control variables. Firms in the matched sample: 547. Firms in columns 3 and 7: 311. Firms in columns 4 and 8: 236. Robust standard errors are clustered by firm (in parentheses). The matched sample is constructed using nearest-neighbor matching with scores given by a probit model in which the dependent variable is *Dummy for high-tech*. The propensity score is estimated using the following firm characteristics: *Ln(Optvol)*, *InstOwn*, *Ln(K/L)*, *Ln(Sales)*, *Ln(Age)*, *Ln(R&D stock)*, *Illiquidity*, *Leverage*, *Tobin's Q*, *ROA*, *Capex*, *Ln(Analyst coverage)*, and fixed effects. All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11
Options volume and innovation–Within-firm relationship

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Post	0.370**		0.277*	
	(0.146)		(0.118)	
Inclusion year −3		0.240		0.008
		(0.154)		(0.080)
Inclusion year −2		0.207		0.084
		(0.144)		(0.075)
Inclusion year −1		0.313**		0.135
		(0.142)		(0.098)
Inclusion year 1		0.243*		0.116
		(0.131)		(0.078)
Inclusion year 2		0.568***		0.271***
		(0.148)		(0.103)
Inclusion year 3		0.636***		0.335***
		(0.145)		(0.114)
Inclusion year 4		0.558***		0.526***
		(0.162)		(0.124)
InstOwn	-0.088	0.010	-0.159	-0.111
	(0.257)	(0.256)	(0.245)	(0.241)
Ln(K/L)	-0.058	-0.061	-0.011	-0.014
	(0.073)	(0.074)	(0.061)	(0.062)
Ln(Sales)	0.196***	0.198***	0.133***	0.134***
	(0.052)	(0.053)	(0.044)	(0.045)
Ln(Age)	-0.225**	-0.225**	-0.072	-0.070
	(0.112)	(0.112)	(0.087)	(0.087)
Ln(R&D stock)	0.211***	0.218***	0.252***	0.255***
	(0.043)	(0.044)	(0.048)	(0.048)
Observations	744	614	744	614

This table presents estimates of OLS panel regressions of within-firm changes in patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) before and after the option listing event. *Post* is a dummy variable equal to unity to indicate the post-listing period; *Inclusion year #* are dummy variables indicating the relative year around the listing event (the omitted category is the year of the event). Firms in columns: 93. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12
Options volume and innovation–Open interest as instrumental variable

Method	OLS (first stage)	2SLS (second stage)	
Dependent Var.	Ln(Optvol)	Ln(1+CITES)	Ln(1+PATS)
	(1)	(2)	(3)
Ln(Optvol) *(instr.)*		0.087***	0.102***
		(0.029)	(0.024)
InstOwn	1.185***	-0.028	-0.218
	(0.140)	(0.156)	(0.137)
Ln(K/L)	-0.205***	0.015	0.039
	(0.053)	(0.053)	(0.045)
Ln(Sales)	0.242***	0.156***	0.133***
	(0.028)	(0.041)	(0.033)
Ln(Age)	-0.412***	-0.121	-0.036
	(0.065)	(0.083)	(0.068)
Ln(R&D stock)	0.056**	0.273***	0.217***
	(0.028)	(0.046)	(0.044)
Ln(Open int.)	1.207***		
	(0.028)		
Observations	3,271	3,271	3,271

This table presents estimates of 2SLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables, with the total open interest *Ln(Open int.)* as an instrumental variable. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13
Options volume and innovation–Managerial entrenchment (E-Index)

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)		-0.032**		-0.031**
x E-Index		(0.015)		(0.013)
Ln(Optvol)	0.168***	0.160***	0.151***	0.144***
	(0.031)	(0.031)	(0.028)	(0.028)
E-Index	-0.014	0.012	-0.016	0.009
(entrenchment index)	(0.034)	(0.034)	(0.029)	(0.029)
InstOwn	-0.020	-0.048	-0.015	-0.041
	(0.192)	(0.193)	(0.170)	(0.170)
Ln(K/L)	0.106	0.107	0.075	0.076
	(0.070)	(0.069)	(0.059)	(0.058)
Ln(Sales)	0.108**	0.103**	0.126***	0.120***
	(0.047)	(0.047)	(0.044)	(0.044)
Ln(Age)	-0.183**	-0.173*	-0.106	-0.098
	(0.090)	(0.090)	(0.084)	(0.084)
Ln(R&D stock)	0.126***	0.124***	0.116***	0.114***
	(0.028)	(0.028)	(0.024)	(0.024)
Observations	921	921	921	921

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*), managerial entrenchment (*E-Index*), their interaction, and other firm-level control variables. Firms in columns: 331. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of three-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The E-Index is an average of six provisions in the firm's charter (see Bebchuk, Cohen, and Ferrell, 2009). The measure is based on data from RiskMetrics from 1998, 2000, 2002, and 2004. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14
Innovation and Tobin's Q

Dependent var.: Tobin's Q Method: OLS	(1)	(2)
Ln(1+CITES)	0.050*	
	(0.026)	
Ln(1+PATS)		0.059*
		(0.033)
One-year lagged Tobin's Q	0.383***	0.383***
	(0.049)	(0.049)
Ln(Optvol)	0.236***	0.236***
	(0.037)	(0.037)
InstOwn	-0.052	-0.041
	(0.202)	(0.202)
Ln(K/L)	0.057	0.054
	(0.106)	(0.106)
Ln(Sales)	-0.221***	-0.225***
	(0.069)	(0.071)
Ln(Age)	-0.173	-0.175
	(0.112)	(0.111)
Ln(R&D stock)	0.030	0.028
	(0.039)	(0.039)
Leverage	-1.625***	-1.610***
	(0.297)	(0.295)
ROA	1.823***	1.830***
	(0.641)	(0.638)
Capex	0.598	0.634
	(2.470)	(2.476)
Observations	2,658	2,658

This table presents estimates of OLS regressions of firms' market value (*Tobin's Q*) on firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*), *one-year lagged Tobin's Q*, options volume (*Optvol*), and other firm-level control variables. Firms in all columns: 526. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. The time period is 1996–2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15
Controlling for possible mechanisms

Dependent Var.	Ln(1+CITES)		Ln(1+PATS)	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)	0.216***	0.154***	0.192***	0.155***
	(0.050)	(0.050)	(0.042)	(0.043)
Competition		8.454***		5.384***
(1 − Lerner)		(2.619)		(1.764)
G-Index		-0.033		-0.032
(governance index)		(0.028)		(0.025)
Ln(CEO age)		-0.807**		-0.605*
		(0.396)		(0.325)
Δ ROA$_{t-1}$		-0.162		-0.123
		(0.406)		(0.307)
Ln(CEO vega)		0.038		0.113***
		(0.054)		(0.041)
Ln(CEO delta)		0.072		0.044
		(0.055)		(0.046)
InstOwn	-0.072	-0.092	-0.139	-0.145
	(0.293)	(0.296)	(0.259)	(0.266)
Ln(K/L)	0.023	0.055	0.079	0.099
	(0.102)	(0.101)	(0.084)	(0.080)
Ln(Sales)	0.231***	0.248***	0.227***	0.240***
	(0.082)	(0.080)	(0.072)	(0.071)
Ln(Age)	-0.147	-0.122	-0.102	-0.068
	(0.154)	(0.154)	(0.142)	(0.140)
Ln(R&D stock)	0.140**	0.142**	0.080	0.082
	(0.062)	(0.061)	(0.059)	(0.058)
Observations	1,530	1,530	1,530	1,530

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on product market competition (*Competition*), managerial entrenchment (*G-Index*), *CEO age*, lagged change in profitability (Δ ROA_{t-1}), stock-based compensation (*CEO vega* and *CEO delta*), and other firm-level control variables. Firms in columns: 285. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16
Descriptive statistics (robustness tests)

	Mean	StdDev	Min	Median	Max	Observations	Source
Co-patents/Patents$_{[t-5,t-1]}$	0.03	0.09	0	0	1	2,391	USPTO
Leverage	0.16	0.16	0	0.13	0.91	3,271	Compustat
Tobin's Q	3.0	2.8	0.40	2.1	39.1	3,271	Compustat
Capex/Assets	0.05	0.05	0.00003	0.04	0.53	3,271	Compustat
Acquisition exp. (in $m)	85.1	458	-3,557	0	8,800	3,271	Compustat
Open interest	396	1,056	0.03	92.4	13,267	3,271	OptionMetrics
Stock illiquidity	-5.5	2.1	-11.6	-5.5	2.9	3,271	TAQ
Analyst coverage	8.4	7.9	0	6.1	45.6	3,271	I/B/E/S
R&D alliances$_{[t-5,t-1]}$	3.7	15.2	0	0	270	1,446	SDC Platinum
Entrenchment index	2.1	1.1	0	2	5	921	RiskMetrics and Bebchuk et al. (2009)
CEO tenure	7.3	7.9	0	5	53	1,845	ExecuComp
CEO cash comp. (in $000s)	1,340	1,492	0	962	43,512	1,845	ExecuComp

Appendix B

Appendix for "The Effect of Patent Protection on Inventor Mobility"

This Appendix provides additional material to the results presented in *"The Effect of Patent Protection on Inventor Mobility."* In Section B.1, we present evidence that supplement the picture that the assignment of applications to examiners is plausibly random. In Section B.2, we discuss and report robustness checks for the first stage estimates. In Section B.3, we report the results of the robustness tests referred in Section 3.5.3 of the article. Descriptive statistics for variables used in this Appendix are presented in B.4.

B.1 Investigating selection

The details of the examination process described in Section 3.4.2 of the article suggest that patent applications are assigned to examiners quasi-randomly within art units. Here, we provide further evidence that our proposed instrument (at the patent level) satisfies the exclusion restriction. For this restriction to hold, examiner leniency should only be related with inventor mobility through its influence on the probability that her patent application is granted. Therefore, we aim to test whether there is any correlation between the characteristics of patent applications (at the time of filing) that can be related with the likelihood that their authors move firms and our measure of examiner leniency (at the patent level). As discussed by Lemley and Sampat (2012), the assessment of whether a certain type of inventions are assigned to examiners with a certain leniency is challenging for two reasons: (i) it is difficult to identify variables that at the time of application would capture the characteristics of the underlying invention and (ii) much of the front-page information contained in patent documents is not available for applications.

One of the most important characteristics of patent applications that can affect the probability of their inventors to move is the value of the underlying innovation, since it is correlated with the inventors? ability (Palomeras and Melero, 2010; Ganco, Ziedonis, and Agarwal, 2015). Though the most common measure to proxy for value of patented innovations (e.g. citations received) is not available at the time of application and, therefore, is not useful for our purposes, there is an alternative proxy for value that it is available at filing. This is the *patent family size*, i.e. the number of jurisdictions in which the application is filed. Because of the substantially higher costs of filing, one expects that applicants are more likely to seek broad international protection only if the invention is economically relevant (Putnam, 1996). Prior literature provides evidence that family size is correlated with a quality index of patents (Lanjouw and Schankerman, 2004), the likelihood that a patent will be granted (Guellec and van Pottelsberghe de la Potterie, 2000) and the economic value of patent rights (Harhoff, Scherer, and Vopel, 2003). We define a patent family in terms of patent equivalents, using as our measure of family size the number of unique jurisdictions in which the focal U.S. patent application was filed at the time of application and protecting the same invention. We construct this measure using the algorithm described in Martinez (2010) on the data extracted from the Worldwide Patent Statistical Database (Patstat, April 2012 edition). We are able to recover this information for all of our patent applications filed between 2001 and 2011 provided that, by January 2012, they were made public (patent applications are made public after 18 months from application or at the resolution date if this happens before). The final sample results in 329,666 observations for which we have non-missing values for examiner leniency and application data. We report the results of the OLS regression of *family size* on *examiner leniency* (as described in Section 3.4.2) in Column 1 of Table B.1. We use art-unit fixed-effects in order to control for potential patterns regarding family size across technologies. We find that the key coefficient on examiner is small (0.003) and insignificant (p-value = 0.877), suggesting that more lenient examiners are unlikely to be systematically assigned more valuable patent applications.

Another used measure for value of (potentially) patented innovations is the number of backward references. A relatively high number of references to previous patents and non-patent literature may indicate innovations of relatively high value, although this is not entirely unambiguous (see Harhoff, Scherer, and Vopel, 2003). Given the importance of cited prior art in later litigation, the idea is that an applicant who seeks to protect a more valuable invention might have incentives to delineate the patent claims by inserting more references to prior art. Note that U.S. patent law imposes a duty of candor on patent applicants to disclose to the Patent Office any information that is "material" to the issuance of the patent (see 37 C.F.R. 1.56). A failure to do so may render the resulting patent unenforceable. We use then the number of applicant-submitted references to patent and non-patent literature at the time of filing available in Patstat. This data is only available though for the subset of applications that are eventually issued as patents. Also in this case, results suggest that there is no clear evidence that more lenient examiners get assigned applications that could protect potentially more valuable innovations.

Finally, we test whether there might be selection based on applicants' size, since this may be a factor that could influence the likelihood of inventors to move. We use as a proxy for size the number of patent applications the applicant filed in the previous year. The last column of Table B.1 report an insignificant coefficient on examiner leniency.

Table B.1
Examiner leniency and application characteristics

Dependent variable Estimation method: OLS	Family size (1)	Applicant PAT References (2)	Applicant NPL References (3)	Applicant APP Volume$_{t-1}$ (4)
Examiner leniency	0.003	0.433	0.223	-37.600
	(0.022)	(0.347)	(0.271)	(26.413)
Filing year FE	Yes***	Yes***	Yes***	Yes***
Art unit FE	Yes***	Yes***	Yes***	Yes***
N	329,666	164,832	164,832	341,007
# of examiners	9,855	7,629	7,629	9,918

Estimation period is 2001 – 2011 in columns 1 to 3 and 2002 – 2011 in columns 4 and 5. Robust standard errors are clustered by examiner (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Robustness tests for the first stage results

In this Appendix, we test whether our measure of examiner leniency (at the patent level) may be driven by technological effects within an art unit. Even though art units correspond to quite delimited technological areas, there may be subareas within an art unit that differ in the patentability of their applications. We can only distinguish these technological sub-areas by looking at the classes and subclasses to which the application is assigned to. Though art units are typically a more fine-grained classification of technologies (there are more art units than technological classes), in some cases there may co-exist different classes or, more frequently, different subclasses in an art unit (see https://www.uspto.gov/web/patents/classification). Therefore, we want to rule out that part of the variation in the measured leniency across examiners may be due to the variation in grant rates across technological (sub)classes within an art unit. This issue is particularly important because we do not conduct our analysis at the patent level but at the inventor level (i.e., we aggregate our relative leniency measure over the applications filed by a given inventor up to a given moment of time), and therefore we cannot include (sub)class fixed-effects in our empirical specifications. We explore whether the aforementioned technological effects may be a concern for our measure of examiner leniency by testing whether the correlation between examiner leniency and patent grant varies substantially when we include more fine-grained technological controls. Table B.2 contains the results from this robustness test. Column 1 contains the baseline correlation between examiner leniency and patent grant without introducing any technological control. Note that our examiner leniency measure is constructed relative to the art unit and year [see Eq. (3.2) and (3.4) of the paper]. This is why we obtain a very similar coefficient when we introduce fixed effects by art unit and year (column 2). Column 3 introduces art unit, year and class fixed effects, in order to control for the effects of classes that either expand over different art units or that share the art unit with another class. Next, we control for the most stringent fixed effects, at the art-unit, year and sub-class level (note that sub-classes are nested in classes). Across all these more stringent specifications, the correlation of examiner leniency and patent grant does not present substantial variations with respect to the baseline model, suggesting that our leniency measure is not the result of differences in the patentability across technological areas inside an art unit.

Table B.2
Technology classification, examiner leniency and patent grants

Dependent variable: Patent grant				
Technology FE included	None	Art unit × Filing year	Art unit × USPC class × Filing year	Art unit × Sub-class × Filing year
Estimation method: OLS	(1)	(2)	(3)	(4)
Examiner leniency	0.737***	0.736***	0.720***	0.741***
	(0.008)	(0.006)	(0.006)	(0.011)

$N = 353,976$. Number of examiners: 10,142. Number of art-units: 626. Number of USPC classes: 413. Number of sub-classes: 41,898. Estimation period is 2001 – 2011. Robust standard errors are clustered by examiner (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Other robustness tests

In this section, we present additional regression results corresponding to the robustness tests referred in Section 3.5.3 of the article.

Table B.3
Patent grants and inventor mobility–Miscellaneous robustness tests

Estimation method: 2SLS		1^{st} dec.	Active			
Sample	All	up to 2006	firms	All	All	All
Dependent variable: Move	(1)	(2)	(3)	(4)	(5)	(6)
# of patents issued *(instr.)*	-0.028***	-0.021***	-0.029***	-0.044**	-0.028***	-0.026***
	(0.006)	(0.008)	(0.006)	(0.019)	(0.006)	(0.008)
# of patents issued				0.002		
× # of patents issued *(instr.)*				(0.002)		
Litigiousness					-0.001**	0.008
					(0.001)	(0.019)
# of patents issued						-0.003
× Litigiousness *(instr.)*						(0.007)
Refined (2-digit) Tech class FE	Yes***					
N	131,485	69,069	130,082	131,485	131,485	131485
# of inventors	69,136	36,403	68,065	69,136	69,136	69,136
# of firms	2,883	2,115	2,471	2,883	2,883	2,883

Robust standard errors are clustered by inventor (in parentheses). All regressions control for the number of years passed since inventor's first decision (log), and fixed effects for the number of applications filed by the inventor and the year of inventor's first decision. Technology field fixed effects use six categories in columns 2 through 6, and 37 sub-categories in column 1. *Litigiousness* is defined as the moving sum of the number of unique patent infringement lawsuits initiated by the source firm from year $t-1$ to year $t-3$ (see Ganco, Ziedonis, and Agarwal, 2015). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4
Patent claims and inventor mobility

Sample	All	All	All	Patents	Patents	Patents
Estimation method	OLS	OLS (1st st.)	2SLS (2nd st.)	OLS	OLS (1st st.)	2SLS (2nd st.)
Dependent variable	Move	Avg. # of claims iss.	Move	Move	Avg. # of claims iss.	Move
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. # of claims issued	-0.001***			0.000		
	(0.000)			(0.000)		
Examiner lenciency		18.075***			12.415***	
		(0.355)			(0.426)	
Avg. # of claims issued *(instr.)*			-0.003***			-0.002**
			(0.001)			(0.001)
First-stage F-statistic		2,721			566	

$N = 131,485$ $(111,921$ in column $4 - 6)$. Number of inventors: 69,136 (57,926 in column 4 – 6). Number of firms: 2,883 (2,567 in column 4 – 6). Estimation period is 2001 – 2011. Robust standard errors are clustered by inventor (in parentheses). All regressions control for the number of years passed since inventor's first decision (log), and fixed effects for the number of applications filed by the inventor and the year of inventor's first decision. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Descriptive statistics

Table B.5
Descriptive statistics (Robustness tests)

Variable	Mean	SD	Min	Median	Max	Observations
Application-level characteristics						
Family size	1.5	1.7	0	1	27	329,666
Applicant PAT references	4.3	13.4	0	0	105	164,832
Applicant NPL references	1.5	8.2	0	0	99	164,832
Applicant APP volume$_{t-1}$	1,261	1,840	0	427	7,803	341,007
Inventor-level characteristics						
Litigiousness	0.79	1.5	0	0	10	131,485
Avg. # of claims issued	12.6	8.9	0	11.5	248	131,485

Bibliography

Acs, Z., L. Anselin, and A. Varga (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy 31*(7), 1069–1085.

Acs, Z. and D. Audretsch (1988). Innovation in large and small firms: An empirical analysis. *American Economic Review 78*(4), 678–690.

Admati, A. and P. Pfleiderer (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies 1*(1), 3–40.

Agarwal, R., M. Ganco, and R. Ziedonis (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal 30*(13), 1349–1374.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics 120*(2), 701–728.

Aghion, P., J. Van Reenen, and L. Zingales (2013). Innovation and institutional ownership. *American Economic Review 103*(1), 277–304.

Agrawal, A., J. McHale, and A. Oettl (2014). Why stars matter. NBER Working Paper No. 20012.

Albert, M., D. Avery, F. Narin, and P. McAllister (1991). Direct validation of citation counts as indicators of industrially important patents. *Research Policy 20*(3), 251–259.

Almeida, P. and B. Kogut (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science 45*(7), 905–917.

Amore, M., C. Schneider, and A. Žaldokas (2013). Credit supply and corporate innovation. *Journal of Financial Economics 109*(3), 835–855.

Anton, J. and D. Yao (2002). The sale of ideas: Strategic disclosure, property rights, and contracting. *The Review of Economic Studies 69*(3), 513–531.

Arora, A., M. Ceccagnoli, and W. Cohen (2008). R&D and the patent premium. *International Journal of Industrial Organization 26*(5), 1153–1179.

Arora, A., A. Fosfuri, and A. Gambardella (2001). *Markets for Technology: The Economics of Innovation and Corporate Strategy.* MIT Press, Cambridge, MA.

Arora, A. and A. Gambardella (1990). Complementarity and external linkages: The strategies of the large firms in biotechnology. *The Journal of Industrial Economics 38*(4), 361–379.

Arora, A. and R. Merges (2004). Specialized supply firms, property rights and firm boundaries. *Industrial and Corporate Change 13*(3), 451–475.

Arrow, K. (1962). The economic implications of learning by doing. *The Review of Economic*

Studies *29*(3), 155–173.

Asker, J., J. Farre-Mensa, and A. Ljungqvist (2015). Corporate investment and stock market listing: A puzzle? *Review of Financial Studies* *28*(2), 342–390.

Azzola, A., P. Landoni, and B. Van Looy (2010). Technological collaboration and R&D alliances: An assessment of the impact on the technical and economical performance of EU regions. Unpublished working paper, Politecnico di Milano and KU Leuven.

Balsmeier, B., A. Chavosh, G.-C. Li, G. Fierro, K. Johnson, A. Kaulagi, D. O'Reagan, B. Yeh, and L. Fleming (2015). Automated disambiguation of U.S. patent grants and applications. Unpublished working paper, Fung Institute for Engineering Leadership.

Bebchuk, L., A. Cohen, and A. Ferrell (2009). What matters in corporate governance? *Review of Financial Studies* *22*(2), 783–827.

Becker, G. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy* *70*(5), 9–49.

Belderbos, R., B. Cassiman, D. Faems, B. Leten, and B. Van Looy (2014). Co-ownership of intellectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners. *Research Policy* *43*(5), 841–852.

Bernstein, S. (2015). Does going public affect innovation? *The Journal of Finance* *70*(4), 1365–1403.

Bertrand, M. and S. Mullainathan (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* *111*(5), 1043–1075.

Bessen, J. (2009). Tool for matching assignee names. NBER Patent Data Project User Documentation: Matching Patent Data to Compustat Firms.

Bhattacharya, S. and J. Ritter (1983). Innovation and communication: Signalling with partial disclosure. *The Review of Economic Studies* *50*(2), 331–346.

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal* *31*(4), 36–72.

Blundell, R., R. Griffith, and J. Van Reenen (1999). Market share, market value and innovation in a panel of British manufacturing firms. *The Review of Economic Studies* *66*(3), 529–554.

Blundell, R. and J. Powell (2004). Endogeneity in semiparametric binary response models. *The Review of Economic Studies* *71*(3), 655–679.

Boldrin, M. and D. Levine (2013). The case against patents. *The Journal of Economic Perspectives* *27*(1), 3–22.

Bonacich, P. (1987). Power and centrality: A family of measures. *American Journal of Sociology* *92*(5), 1170–1182.

Bönte, W. and M. Keilbach (2005). Concubinage or marriage? Informal and formal cooperations for innovation. *International Journal of Industrial Organization* *23*(3-4), 279–302.

Budd, C., C. Harris, and J. Vickers (1993). A model of the evolution of duopoly: Does the asymmetry between firms tend to increase or decrease? *The Review of Economic Studies* *60*(3), 543–573.

Bushee, B. (1998). The influence of institutional investors on myopic R&D investment behavior.

The Accounting Review 73(3), 305–333.

Cao, H. (1999). The effect of derivative assets on information acquisition and price behavior in a rational expectations equilibrium. *Review of Financial Studies 12*(1), 131–163.

Cassiman, B. and R. Veugelers (2006). In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. *Management Science 52*(1), 68–82.

Ceccagnoli, M. (2009). Appropriability, preemption, and firm performance. *Strategic Management Journal 30*(1), 81–98.

Chakravarty, S., H. Gulen, and S. Mayhew (2004). Informed trading in stock and option markets. *The Journal of Finance 59*(3), 1235–1257.

Chen, Q., I. Goldstein, and W. Jiang (2007). Price informativeness and investment sensitivity to stock price. *Review of Financial Studies 20*(3), 619–650.

Chowdhry, B. and V. Nanda (1991). Multimarket trading and market liquidity. *Review of Financial Studies 4*(3), 483–511.

Coad, A. and R. Rao (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy 37*(4), 633–648.

Cockburn, I., S. Kortum, and S. Stern (2003). Are all patent examiners created equal? Examiners, patent characteristics and litigation outcomes. In W. Cohen and S. Merril (Eds.), Patents in the Knowledge-Based Economy, pp. 17–53. National Academies Press.

Cogan, G. and R. Burgelman (1989). Intel corporation: The dram decision. Stanford Business School Case Study 9-BP2-56A.

Cohen, W. and R. Levin (1989). Empirical studies of innovation and market structure. In R. Schmalensee and R. Willig (Eds.), Handbook of Industrial Organization, Volume 2, pp. 1059–1107. Elsevier.

Cohen, W., R. Nelson, and J. Walsh (2000). Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not). NBER Working Paper No. 7552.

Coles, J., N. Daniel, and L. Naveen (2006). Managerial incentives and risk-taking. *Journal of Financial Economics 79*(2), 431–468.

Conti, A., J. Thursby, and M. Thursby (2013). Patents as signals for startup financing. *The Journal of Industrial Economics 61*(3), 592–622.

Core, J. and W. Guay (2002). Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting Research 40*(3), 613–630.

Criscuolo, P., O. Alexy, D. Sharapov, and A. Salter (2015). Lifting the veil on patents and inventions. In Academy of Management Proceedings.

Criscuolo, P. and B. Verspagen (2008). Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. *Research Policy 37*(10), 1892–1908.

Czarnitzki, D., K. Hussinger, and B. Leten (2011). The market value of blocking patent citations. ZEW Working Paper No. 11-021.

Datar, S. and C. Reavis (2003). Novartis pharma: The business unit model. Harvard Business School Case Study 9-101-030.

Diestre, L. and N. Rajagopalan (2012). Are all 'sharks' dangerous? New biotechnology ventures and partner selection in R&D alliances. *Strategic Management Journal 33*(10), 1115–1134.

Dow, J. and G. Gorton (1997). Stock market efficiency and economic efficiency: Is there a connection? *The Journal of Finance 52*(3), 1087–1129.

Durnev, A., R. Morck, and B. Yeung (2004). Value-enhancing capital budgeting and firm-specific stock return variation. *The Journal of Finance 59*(1), 65–105.

Dyer, J. and H. Singh (1998). The relational view: Cooperative strategy and sources of inter-organizational competitive advantage. *Academy of Management Review 23*(4), 660–679.

Easley, D., M. O'Hara, and P. Srinivas (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance 53*(2), 431–465.

Edmans, A., X. Gabaix, and A. Landier (2009). A multiplicative model of optimal CEO incentives in market equilibrium. *Review of Financial Studies 22*(12), 4881–4917.

Edmans, A. and G. Manso (2011). Governance through trading and intervention: A theory of multiple blockholders. *Review of Financial Studies 24*(7), 2395–2428.

Fallick, B., C. Fleischman, and J. Rebitzer (2006). Job-hopping in silicon valley: Some evidence concerning the microfoundations of a high-technology cluster. *The Review of Economics and Statistics 88*(3), 472–481.

Fang, V., X. Tian, and S. Tice (2014). Does stock liquidity enhance or impede firm innovation? *The Journal of Finance 69*(5), 2085–2125.

Farre-Mensa, J., D. Hegde, and A. Ljungqvist (2017). What is a patent worth? Evidence from the U.S. patent lottery. NBER Working Paper No. 23268.

Faure-Grimaud, A. and D. Gromb (2004). Public trading and private incentives. *Review of Financial Studies 17*(4), 985–1014.

Federal Trade Commission (2003). To promote innovation: The proper balance of competition and patent law and policy.

Ferreira, D., M. Ferreira, and C. Raposo (2011). Board structure and price informativeness. *Journal of Financial Economics 99*(3), 523–545.

Fleming, L. and O. Sorenson (2004). Science as a map in technological search. *Strategic Management Journal 25*(8-9), 909–928.

Fosfuri, A., C. Helmers, and C. Roux (2012). Are joint patents collusive? Evidence from the U.S. and Europe. Unpublished working paper, Bocconi University, Universidad Carlos III de Madrid, and University of St. Gallen.

Fosfuri, A., M. Motta, and T. Rønde (2001). Foreign direct investment and spillovers through workers mobility. *Journal of International Economics 53*(1), 205–222.

Foucault, T. and T. Gehrig (2008). Stock price informativeness, cross-listings, and investment decisions. *Journal of Financial Economics 88*(1), 146–168.

Frakes, M. and M. Wasserman (2016). Patent office cohorts. *Duke Law Journal 65*(8), 1601–1655.

Francis, B., I. Hasan, and Z. Sharma (2011). Incentives and innovation: Evidence from CEO compensation contracts. Unpublished working paper, Rensselaer Polytechnic Institute, Fordham University, and Long Island University.

Freeman, C. and L. Soete (1997). *The Economics of Industrial Innovation.* MIT Press, Cambridge, MA.

Galasso, A. and M. Schankerman (2015). Patents and cumulative innovation: Causal evidence from the courts. *The Quarterly Journal of Economics 130*(1), 317–369.

Ganco, M., R. Ziedonis, and R. Agarwal (2015). More stars stay, but the brightest ones still leave: Job hopping in the shadow of patent enforcement. *Strategic Management Journal 36*(5), 659–685.

Gans, J., D. Hsu, and S. Stern (2002). When does start-up innovation spur the gale of creative destruction? *The RAND Journal of Economics 33*(4), 571–586.

Gaulé, P. (2015). Patents and the success of venture-capital backed startups: Using examiner assignment to estimate causal effects. Unpublished working paper, Charles University and Economics Institute of the Academy of Sciences of the Czech Republic.

Ge, C., K.-W. Huang, and I. Png (2016). Engineer/scientist careers: Patents, online profiles, and misclassification bias. *Strategic Management Journal 37*(1), 232–253.

Gibbons, R. and K. Murphy (1992). Optimal incentive contracts in the presence of career concerns: Theory and evidence. *Journal of Political Economy 100*(3), 468–505.

Gillan, S., J. Hartzell, and R. Parrino (2009). Explicit versus implicit contracts: Evidence from CEO employment agreements. *The Journal of Finance 64*(4), 1629–1655.

Gilson, R. J. (1999). The legal infrastructure of high technology industrial districts: Silicon valley, route 128, and covenants not to compete. *New York University Law Review 74*, 575.

Giuri, P., M. Mariani, S. Brusoni, G. Crespi, D. Francoz, A. Gambardella, W. Garcia-Fontes, A. Geuna, R. Gonzales, D. Harhoff, K. Hoisl, C. Le Bas, A. Luzzi, L. Magazzini, L. Nesta, Ö. Nomaler, N. Palomeras, P. Patel, M. Romanelli, and B. Verspagen (2007). Inventors and invention processes in Europe: Results from the PatVal-EU survey. *Research Policy 36*(8), 1107–1127.

Glosten, L. and P. Milgrom (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics 14*(1), 71–100.

Gompers, P., J. Ishii, and A. Metrick (2003). Corporate governance and equity prices. *The Quarterly Journal of Economics 118*(1), 107–156.

Graham, J., C. Harvey, and S. Rajgopal (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics 40*(1-3), 3–73.

Graham, S., A. Marco, and R. Miller (2015). The USPTO patent examination research dataset: A window on the process of patent examination. USPTO Working Paper No. 2015-4.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature 28*(4), 1661–1707.

Grimpe, C. and K. Hussinger (2014). Resource complementarity and value capture in firm acquisitions: The role of intellectual property rights. *Strategic Management Journal 35*(12), 1762–1780.

Guellec, D., C. Martinez, and P. Zuniga (2012). Pre-emptive patenting: Securing market exclusion and freedom of operation. *Economics of Innovation and New Technology 21*(1), 1–29.

Guellec, D. and B. van Pottelsberghe de la Potterie (2000). Applications, grants and the value of patent. *Economics Letters 69*(1), 109–114.

Guellec, D. and B. Van Pottelsberghe de la Potterie (2008). *The Economics of the European Patent System: IP Policy for Innovation and Competition*. Oxford University Press, Oxford, UK.

Gulati, R. (1995). Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. *Academy of Management Journal 38*(1), 85–112.

Gulati, R. and M. Gargiulo (1999). Where do inter-organizational networks come from? *American Journal of Sociology 104*(5), 1439–1493.

Gulati, R. and H. Singh (1998). The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. *Administrative Science Quarterly 43*(4), 781–814.

Hagedoorn, J. (2003). Sharing intellectual property rights – An exploratory study of joint patenting amongst companies. *Industrial and Corporate Change 12*(5), 1035–1050.

Hall, B., A. Jaffe, and M. Trajtenberg (2001). The NBER patent citation data file: Lessons, insights and methodological tools. NBER Working Paper No. 8498.

Hall, B., A. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *The RAND Journal of Economics 36*(1), 16–38.

Hall, B. and J. Lerner (2010). The financing of R&D and innovation. In B. Hall and N. Rosenberg (Eds.), Handbook of The Economics of Innovation, Volume 1, pp. 609–639. Elsevier.

Hamel, G., Y. Doz, and C. Prahalad (1989). Collaborate with your competitors and win. *Harvard Business Review 67*(1), 133–139.

Harhoff, D., K. Hoisl, and C. Webb (2005). Analysing European and international patent citations: A set of EPO patent database building blocks. OECD Working Paper No. 2005/09.

Harhoff, D., F. Narin, F. Scherer, and K. Vopel (1999). Citation frequency and the value of patented inventions. *The Review of Economics and Statistics 81*(3), 511–515.

Harhoff, D. and M. Reitzig (2004). Determinants of opposition against EPO patent grants – the case of biotechnology and pharmaceuticals. *International Journal of Industrial Organization 22*(4), 443–480.

Harhoff, D., F. Scherer, and K. Vopel (2003). Citations, family size, opposition and the value of patent rights. *Research Policy 32*(8), 1343–1363.

Hart, O. (1983). The market mechanism as an incentive scheme. *The Bell Journal of Economics 14*(2), 366–382.

Hausman, J., B. Hall, and Z. Griliches (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica 52*(4), 909–938.

Hayes, R., P. Oyer, and S. Schaefer (2006). Coworker complementarity and the stability of top-management teams. *Journal of Law, Economics, and Organization 22*(1), 184–212.

He, J. and X. Tian (2013). The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics 109*(3), 856–878.

Hegde, D. (2014). Tacit knowledge and the structure of license contracts: Evidence from the biomedical industry. *Journal of Economics & Management Strategy 23*(3), 568–600.

Heller, M. and R. Eisenberg (1998). Can patents deter innovation? The anticommons in biomedical research. *Science 280*(5364), 698–701.

Hirshleifer, D., A. Low, and S. Teoh (2012). Are overconfident CEOs better innovators? *The Journal of Finance 67*(4), 1457–1498.

Hitt, M., L. Bierman, K. Uhlenbruck, and K. Shimizu (2006). The importance of resources in the internationalization of professional service firms: The good, the bad, and the ugly. *Academy of Management Journal 49*(6), 1137–1157.

Hoang, H. and F. Rothaermel (2005). The effect of general and partner-specific alliance experience on joint R&D project performance. *Academy of Management Journal 48*(2), 332–345.

Hoetker, G. (2007). The use of logit and probit models in strategic management research: Critical issues. *Strategic Management Journal 28*(4), 331–343.

Hoetker, G. and R. Agarwal (2007). Death hurts, but it isn't fatal: The postexit diffusion of knowledge created by innovative companies. *Academy of Management Journal 50*(2), 446–467.

Hohberger, J., P. Almeida, and P. Parada (2015). The direction of firm innovation: The contrasting roles of strategic alliances and individual scientific collaborations. *Research Policy 44*(8), 1473–1487.

Hoisl, K. (2006). A study of inventors: Incentives, productivity, and mobility. Ph. D. Dissertation, University of Munich.

Hoisl, K. (2007). Tracing mobile inventors – The causality between inventor mobility and inventor productivity. *Research Policy 36*(5), 619–636.

Holmström, B. (1989). Agency costs and innovation. *Journal of Economic Behavior & Organization 12*(3), 305–327.

Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. *The Review of Economic Studies 66*(1), 169–182.

Holmström, B. and J. Tirole (1993). Market liquidity and performance monitoring. *Journal of Political Economy 101*(4), 678–709.

Hsu, D. and R. Ziedonis (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal 34*(7), 761–781.

Hsu, P.-H., X. Tian, and Y. Xu (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics 112*(1), 116–135.

Hu, J. (2014). Does option trading convey stock price information? *Journal of Financial Economics 111*(3), 625–645.

Hwang, M. and J. Lin (1999). Information dimension, information overload and decision quality. *Journal of Information Science 25*(3), 213–218.

Jaffe, A. and M. Trajtenberg (2002). *Patents, Citations, and Innovations: A Window on the Knowledge Economy.* MIT Press, Cambridge, MA.

Janowicz-Panjaitan, M. and N. Noorderhaven (2008). Formal and informal inter-organizational learning within strategic alliances. *Research Policy 37*(8), 1337–1355.

Jaravel, X., N. Petkova, and A. Bell (2015). Team-specific capital and innovation. SSRN Working Paper No. 2669060.

Jenter, D. and K. Lewellen (2014). Performance-induced CEO turnover. Unpublished working paper, Stanford University.

Katila, R. and G. Ahuja (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal 45*(6), 1183–1194.

Katila, R., J. Rosenberger, and K. Eisenhardt (2008). Swimming with sharks: Technology ventures, defense mechanisms and corporate relationships. *Administrative Science Quarterly 53*(2), 295–332.

Katila, R. and S. Shane (2005). When does lack of resources make new firms innovative? *Academy of Management Journal 48*(5), 814–829.

Khanna, N., S. Slezak, and M. Bradley (1994). Insider trading, outside search, and resource allocation: Why firms and society may disagree on insider trading restrictions. *Review of Financial Studies 7*(3), 575–608.

Khanna, T., R. Gulati, and N. Nohria (1998). The dynamics of learning alliances: Competition, cooperation, and relative scope. *Strategic Management Journal 19*(3), 193–210.

Kim, J. and G. Marschke (2005). Labor mobility of scientists, technological diffusion, and the firm's patenting decision. *The RAND Journal of Economics 36*(2), 298–317.

Kogut, B. (1988). Joint ventures: Theoretical and empirical perspectives. *Strategic Management Journal 9*(4), 319–332.

Kothari, S. (2001). Capital markets research in accounting. *Journal of Accounting and Economics 31*(1-3), 105–231.

Kyle, A. (1985). Continuous auctions and insider trading. *Econometrica 53*(6), 1315–1335.

Lamoreaux, N. and K. Sokoloff (1999). Inventors, firms, and the market for technology in the late nineteenth and early twentieth centuries. In N. Lamoreaux, D. Raff, and P. Temin (Eds.), *Learning by Doing in Markets, Firms, and Countries*, pp. 19–60. University of Chicago Press.

Lanjouw, J. (1998). Patent protection in the shadow of infringement: Simulation estimations of patent value. *The Review of Economic Studies 65*(4), 671–710.

Lanjouw, J. and M. Schankerman (2001). Characteristics of patent litigation: A window on competition. *The RAND Journal of Economics 32*(1), 129–151.

Lanjouw, J. and M. Schankerman (2004). Protecting intellectual property rights: Are small firms handicapped? *Journal of Law and Economics 47*(1), 45–74.

Lazear, E. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy 117*(5), 914–940.

Lemley, M. and B. Sampat (2012). Examiner characteristics and patent office outcomes. *Review of Economics and Statistics 94*(3), 817–827.

Lerner, J., M. Sorensen, and P. Strömberg (2011). Private equity and long-run investment: The case of innovation. *The Journal of Finance 66*(2), 445–477.

Lerner, J. and J. Wulf (2007). Innovation and incentives: Evidence from corporate R&D. *The Review of Economics and Statistics 89*(4), 634–644.

Levin, R., A. Klevorick, R. Nelson, S. Winter, R. Gilbert, and Z. Griliches (1987). Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity 1987*(3), 783–831.

Lhuillery, S. and E. Pfister (2009). R&D cooperation and failures in innovation projects: Empirical evidence from French CIS data. *Research Policy 38*(1), 45–57.

Li, D., L. Eden, M. Hitt, and D. Ireland (2008). Friends, acquaintances, or strangers? Partner selection in R&D alliances. *Academy of Management Journal 51*(2), 315–334.

Li, G.-C., R. Lai, A. D'Amour, D. Doolin, Y. Sun, V. Torvik, A. Yu, and L. Fleming (2014). Disambiguation and co-authorship networks of the U.S. patent inventor database (1975 – 2010). *Research Policy 43*(6), 941–955.

Lichtman, D. (2004). Rethinking prosecution history estoppel. *The University of Chicago Law Review 71*(1), 151–182.

Lofstrom, S. (2000). Absorptive capacity in strategic alliances: Investigating the effects of individuals' social and human capital on inter-firm learning. Unpublished working paper, University of Maryland.

Long, C. (2002). Patent signals. *University of Chicago Law Review 69*(2), 625–679.

Luo, Y. (2005). Do insiders learn from outsiders? Evidence from mergers and acquisitions. *The Journal of Finance 60*(4), 1951–1982.

Maliranta, M., P. Mohnen, and P. Rouvinen (2009). Is inter-firm labor mobility a channel of knowledge spillovers? evidence from a linked employer–employee panel. *Industrial and Corporate Change 18*(6), 1161–1191.

Mansfield, E. (1986). Patents and innovation: An empirical study. *Management Science 32*(2), 173–181.

Marco, A., A. Myers, S. Graham, P. D'Agostino, and K. Apple (2015). The USPTO patent assignment dataset: Descriptions and analysis. USPTO Working Paper No. 2015-2.

Martinez, C. (2010). Insight into different types of patent families. Organisation for Economic Co-operation and Development Working Paper No. 2010/2.

Marx, M., D. Strumsky, and L. Fleming (2009). Mobility, skills, and the michigan non-compete experiment. *Management Science 55*(6), 875–889.

Maurseth, P. and R. Svensson (2015). Tacit knowledge and the dynamics of inventor activity. Unpublished working paper, Norwegian Business School.

Mayhew, S. and V. Mihov (2004). How do exchanges select stocks for option listing? *The Journal of Finance 59*(1), 447–471.

Moser, P. (2011). Do patents weaken the localization of innovations? Evidence from world's fairs. *The Journal of Economic History 71*(2), 363–382.

Narayanan, M. (1985). Managerial incentives for short-term results. *The Journal of Finance 40*(5), 1469–1484.

Narin, F., K. Hamilton, and D. Olivastro (1997). The increasing linkage between U.S. technology and public science. *Research Policy 26*(3), 317–330.

National Science Foundation (2010). Science and Engineering Indicators 2010. National Science

Foundation NSB No. 10-01.

Nelson, R. and S. Winter (1982). *An evolutionary theory of economic change*. Harvard University Press, Cambridge, MA.

Nerkar, A. and S. Paruchuri (2005). Evolution of R&D capabilities: The role of knowledge networks within a firm. *Management Science 51*(5), 771–785.

Ni, S., J. Pan, and A. Poteshman (2008). Volatility information trading in the option market. *The Journal of Finance 63*(3), 1059–1091.

Nordhaus, W. (1969). An economic theory of technological change. *The American Economic Review 59*(2), 18–28.

Norton, E., H. Wang, and C. Ai (2004). Computing interaction effects and standard errors in logit and probit models. *The Stata Journal 4*(2), 154–167.

O'Reilly, C. (1980). Individuals and information overload in organizations: Is more necessarily better? *Academy of Management Journal 23*(4), 684–696.

Organisation for Economic Co-operation and Development (2011). ISIC Rev. 3 Technology Intensity Definition, Classification of manufacturing industries into categories based on R&D intensities. OECD Publishing, Paris.

Organisation for Economic Co-operation and Development (2013). OECD Science, Technology and Industry Scoreboard. OECD Publishing, Paris.

Oxley, J. (1999). Institutional environment and the mechanisms of governance: The impact of intellectual property protection on the structure of inter-firm alliances. *Journal of Economic Behavior & Organization 38*(3), 283–309.

Oxley, J. and R. Sampson (2004). The scope and governance of international R&D alliances. *Strategic Management Journal 25*(8-9), 723–749.

Oxley, J. and T. Wada (2009). Alliance structure and the scope of knowledge transfer: Evidence from U.S.-Japan agreements. *Management Science 55*(4), 635–649.

Pakes, A. and Z. Griliches (1980). Patents and R&D at the firm level: A first report. *Economics Letters 5*(4), 377–381.

Palomeras, N. and E. Melero (2010). Markets for inventors: Learning-by-hiring as a driver of mobility. *Management Science 56*(5), 881–895.

Pan, J. and A. Poteshman (2006). The information in option volume for future stock prices. *Review of Financial Studies 19*(3), 871–908.

Paruchuri, S. (2010). Intra-organizational networks, inter-organizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science 21*(1), 63–80.

Pezzoni, M., F. Lissoni, and G. Tarasconi (2014). How to kill inventors: Testing the Massacrator© algorithm for inventor disambiguation. *Scientometrics 101*(1), 477–504.

Png, I. and S. Samila (2015). Trade secrets law and mobility: Evidence from "inevitable disclosure". Unpublished working paper, National University of Singapore.

Podolny, J. (2001). Networks as the pipes and prisms of the market. *American Journal of Sociology 107*(1), 33–60.

Podolny, J., T. Stuart, and M. Hannan (1996). Networks, knowledge, and niches: Competition in the worldwide semiconductor industry, 1984-1991. *American Journal of Sociology 102*(3), 659–689.

Porter, M. (1992). Capital disadvantage: America's failing capital investment system. *Harvard Business Review 70*(5), 65–82.

Putnam, J. (1996). The value of international patent protection. Ph. D. Dissertation, Yale University.

Reuer, J. and S. Devarakonda (2012). Beyond contracts: Governing structures in non-equity alliances. In Academy of Management Proceedings.

Robinson, D. and T. Stuart (2007). Network effects in the governance of strategic alliances. *Journal of Law, Economics, and Organization 23*(1), 242–273.

Roll, R., E. Schwartz, and A. Subrahmanyam (2009). Options trading activity and firm valuation. *Journal of Financial Economics 94*(3), 345–360.

Rosenbaum, P. and D. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*(1), 41–55.

Rosenbaum, P. and D. Rubin (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association 79*(387), 516–524.

Rosenkopf, L. and P. Almeida (2003). Overcoming local search through alliances and mobility. *Management Science 49*(6), 751–766.

Ross, S. (1976). Options and efficiency. *The Quarterly Journal of Economics 90*(1), 75–89.

Rothaermel, F. and M. Alexandre (2009). Ambidexterity in technology sourcing: The moderating role of absorptive capacity. *Organization Science 20*(4), 759–780.

Sampat, B. and H. Williams (2015). How do patents affect follow-on innovation? Evidence from the human genome. NBER Working Paper No. 21666.

Sampson, R. (2007). R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal 50*(2), 364–386.

Schmidt, K. (1997). Managerial incentives and product market competition. *The Review of Economic Studies 64*(2), 191–213.

Schönberg, U. (2007). Testing for asymmetric employer learning. *Journal of Labor Economics 25*(4), 651–691.

Shleifer, A. and R. Vishny (1990). Equilibrium short horizons of investors and firms. *American Economic Review 80*(2), 148–153.

Singh, J. (2007). Asymmetry of knowledge spillovers between MNCs and host country firms. *Journal of International Business Studies 38*(5), 764–786.

Singh, J. and A. Agrawal (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science 57*(1), 129–150.

Song, J., P. Almeida, and G. Wu (2003). Learning-by-hiring: When is mobility more likely to facilitate inter-firm knowledge transfer? *Management Science 49*(4), 351–365.

Starr, E. (2016). Consider this: Training, wages, and the enforceability of covenants not to compete. SSRN Working Paper No. 2556669.

Stein, J. (1988). Takeover threats and managerial myopia. *Journal of Political Economy 96*(1), 61–80.

Stein, J. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *The Quarterly Journal of Economics 104*(4), 655–669.

Stock, J. and M. Yogo (2005). Testing for weak instruments in linear iv regression. In D. Andrews (Ed.), *Identification and Inference for Econometric Models*, pp. 80–108. Cambridge University Press.

Subrahmanyam, A. and S. Titman (1999). The going-public decision and the development of financial markets. *The Journal of Finance 54*(3), 1045–1082.

Teece, D. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy 15*(6), 285–305.

Tian, X. and T. Wang (2014). Tolerance for failure and corporate innovation. *Review of Financial Studies 27*(1), 211–255.

Toivanen, O. and L. Väänänen (2012). Returns to inventors. *Review of Economics and Statistics 94*(4), 1173–1190.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The RAND Journal of Economics 21*(1), 172–187.

Trajtenberg, M., G. Shiff, and R. Melamed (2006). The "Names Game:" Harnessing inventors' patent data for economic research". NBER Working Paper No. 12479.

Van Looy, B., M. du Plessis, and T. Magerman (2006). Data production methods for harmonised patent statistics: Assignee sector allocation. KU Leuven MSI Working Paper No. 0605.

Von Graevenitz, G., S. Wagner, and D. Harhoff (2013). Incidence and growth of patent thickets: The impact of technological opportunities and complexity. *The Journal of Industrial Economics 61*(3), 521–563.

Wang, X. (2015). Essays on the internal dynamics of an R&D alliance – What determines the individuals' contribution to the alliance? Ph. D. Dissertation, University of Groningen.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press, Cambridge, MA.

Wooldridge, J. (2014). Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. *Journal of Econometrics 182*(1), 226–234.

Ziedonis, R. (2004). Don't fence me in: Fragmented markets for technology and the patent acquisition strategies of firms. *Management Science 50*(6), 804–820.

Zucker, L., M. Darby, and M. Torero (2002). Labor mobility from academe to commerce. *Journal of Labor Economics 20*(3), 629–660.